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Channel Reduction in Massive Array Parallel MRI

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Abstract— **This paper presents a method to explore the flexibility of channel reduction in k-domain parallel imaging with massive arrays to improve the computation efficiency. MCMLI and GRAPPA are k-domain reconstruction methods that use a neighborhood of PE columns, FE line(s) and all channels in the interpolation kernels. For massive array which contains a large number of element coils computation cost can be a significant problem. In this paper, channel selection and reduction is performed according to the correlation between channel images for individual channel reconstructions. Simulation results show that the proposed channel reduction algorithm can achieve similar or improved reconstruction quality with significantly reduced computation for massive arrays with localized sensitivity.**

I. INTRODUCTION

Partial parallel imaging (PPI) MRI using coil arrays and multiple receivers can speed up data acquisition time by acquiring a reduced set of data [1-5,8,9,11]. Many approaches have been proposed to reconstruct original object image utilizing sensitivity information of multiple channels.

One criterion that can be used to categorize these methods is whether they ask for an accurate estimate of channel sensitivities. Methods such as sensitivity encoding (SENSE) [9] and simultaneous acquisition of spatial harmonics (SMASH) [2] belong to the first category that needs prior knowledge of channel sensitivity. While methods such as AUTO-SMASH [3], variable density AUTO-SMASH (VD-AUTO-SMASH) [4], generalized auto-calibration partially parallel acquisitions (GRAPPA) [5] and multicolumn multiline interpolation (MCMLI) [8] rely on autocalibration data and do not need sensitivity information.

In SENSE, the reconstruction problem can be formulated as solving a matrix inverse problem. While in MCMLI, missed data points of all channels are reconstructed using data interpolation. In addition, in MCMLI, to reconstruct one channel, data points of all channels are used in the interpolation. Hence the computation costs of these two methods are approximately proportional to the number of channels N_c and N_c^2 respectively [11,12]. In PPI with massive arrays [7] which contains a large number of element coils, computation cost of parallel reconstruction can be a significant.

Several approaches have been proposed to reduce the computation cost for massive arrays with localized sensitivity. For SENSE, the sensitivity matrix can be truncated, or the coil set can be reduced, to a smaller size using singular value decomposition [10,12]. However, in localized array, due to the incomplete local information contained in each channel, all channels have to be kept and used for reconstruction.

The optimal kernel size, number of neighbor blocks, columns and channels, is dependent on many factors such as FOV, coil array configuration, sub-sampling direction and the width of coil sensitivity. A method that tried to obtain the optimal kernel by decomposing of a larger kernel [6] can be employed to reduce MCMLI computation cost in massive array. However, as the coil sensitivity used in massive array is localized and the acquired data of each channel only contains information of the object around coil center, a more straight forward way to reduce computation cost is to set the kernel of MCMLI cover only a small set of channels in neighborhood, as original proposed in [13] and recently further reported in [14,15].

In this work, it is shown that this small kernel can achieve a reconstruction quality almost the same as that of a kernel contains all channels, but with significantly reduced reconstruction time. A process of selecting neighbor channels for MCMLI kernel is based on the correlation between the source channel and the target channel.

II. MATERIALS AND THEORY

1. *Reconstruction Using MCMLI*

In general, MCMLI is an improved data reconstruction method for generalized autocalibrating partially parallel acquisition which employs not only neighbor data points along PE direction but also those along the FE direction.

Received k-space signal is noted as S, the k-space coordinate noted as (k_y, k_x) and the sampling intervals along k_y and k_x axis noted as Δk_y and Δk_x, and the process of MCMLI can be represented by [8]:

$$S_j(k_y + r\Delta k_y, k_x) = \sum_{l=1}^{L} \sum_{b=-N_b}^{N_b} \sum_{h=-H_l}^{H_r} W_{j,r}(l,b,h) \times S_l(k_y + bR\Delta k_y, k_x + h\Delta k_x) \quad (1)$$

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where j represents the j-th channel, R is the acceleration factor, and $r(r = 1,...,R)$ is the relative location of current data point being interpolated inside its block. N_b is the number of neighbor blocks and H_l, H_r are number of neighbor columns used on each side. L is the total number of channels. $W_{j,r}$ refers to the net weights of the *r-th* net weights to target channel j.

Equation (1) represents relation of one data and its 3-D neighbor data points. A general form for the *r-th* net can be written as,

$$\mathbf{S}_{target} = \mathbf{S}_{source}\mathbf{W}_r, \; r = 1,..,R-1 \qquad (2)$$

where $\mathbf{W}_r$ is the weight vector of length $L \times 2N_b \times (H_l + H_r)$, $\mathbf{S}_{target}$ is the unknown data and $\mathbf{S}_{source}$ is the sampled data. MCMLI has two steps: weights calibration and interpolation. In the first step, auto-calibration signals (ACS) fully sampled PE lines in central k-space are used as training data to calculate weight vector $\mathbf{W}_r$ ($\mathbf{S}_{target}$ and $\mathbf{S}_{source}$ are known then LMS solution of $\mathbf{W}_r$ is obtained). In the following step, all sub-sampled missing points belonging to the *r-th* net are interpolated using obtained weight vector ($\mathbf{S}_{target}$ is unknown). In conclusion, this method reconstructs missed data of each channel using data from all the channels.

2. *Channel Reduction Utilizing Sensitivity Locality*

In MCMLI, the weight vector has a length proportional to number of total channels. This may lead to huge computation cost in massive arrays due to the large number of channels. In the case that channel sensitivity is localized compared to FOV, data of each channel contains information of only a part of the object. Two far distanced channels contain little information of each other and interpolating one with the data from the other will only introduce more noise. Thus, channel reduction is possible to be performed using this locality of channel sensitivity.

The idea of channel reduction is to keep only a small set of neighbor channels which are better correlated with the channel being reconstructed. Irrelevant channels with little information will be dropped and contribute nothing. The reconstruction of using this small set of channels is expected to achieve the same quality as using all. From another prospective of view, when using all channels to reconstruct one, those irrelevant channels are more likely to be assigned a set of coefficients of smaller value and can be almost taken as dropped.

Assume that on average N_c channels were selected for each channel. The total computation and memory complexity will be reduced by a factor of $O((N_c / C)^p)$ 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.

Channel reduction number N_c is mainly determined by SNR and accelerating factor. In general, keeping all other factors unchanged, an increase of accelerating factor needs at least the same amount of increase of N_c in reconstruction.

3. *Correlation Estimate*

As stated above, correlation between channels are used as criteria to perform channel reduction. By acquiring prior fully sampled data, channel sensitivities can be estimated and then correlations are obtained. Or simply, we can calculate the correlation of individual channel images instead. However, this procedure requires additional data acquisition.

In PPI, to skip this step, we consider to use individual channel images which are aliased due to down sampling of k-space data. The aliased object in channel images can lead to inaccurate correlation estimation as illustrated in Fig.1 (a). But for MCMLI reconstruction, correlation estimate procedure can be incorporated correctly into the reconstruction step with the help of ACS. ACS are fully sampled data located in the central k-space and possesses most of the image power. So in channel images of a down sampled data with ACS, aliasing effect is only from high frequency component of lower energy as shown in Fig.1 (b). Then the correlation estimate error caused by aliasing effect can be omitted.

Correlation coefficient between aliased channel images is defined as:

$$\rho(m,n) = \mathrm{cov}(I_m, I_n) / (\sigma_m \sigma_n) \qquad (3)$$

where m,n are channel indices, σ_m and σ_n are standard deviations of each image. Then an empirical threshold was used to select a subset of coils that will be used in reconstruction of each individual channels.

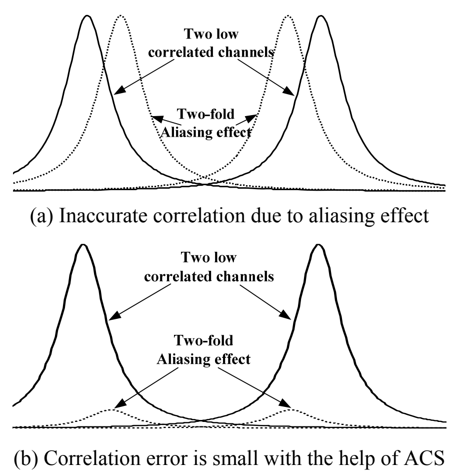


Fig.1 Illustration of inaccurate correlation problem which is addressed with the existence of ACS

III. METHOD AND RESULTS

K-space sub-sampling and reconstruction with MCMLI were performed using both simulated data and in vivo array imaging data. Phase encoding lines were partially decimated to simulate the PPI procedure and then reconstructed. This entire MCMLI reconstruction procedure was performed offline using MATLAB (Math Works, Natick, MA).

Simulated data was generated using a 64-element array of planar pair coils [7] as shown in Fig.2 (a). Channel sensitivity of each channel was calculated according to Biot-Savart equation. K-space data was then obtained by modulating a standard Shepp-Logan phantom with generated array sensitivities. Accelerating direction was along the PE direction aligned with array. Several sets of data with different depth as shown in Fig.2 (b), namely different sensitivity width, were used to test effects of correlations on channel reduction.

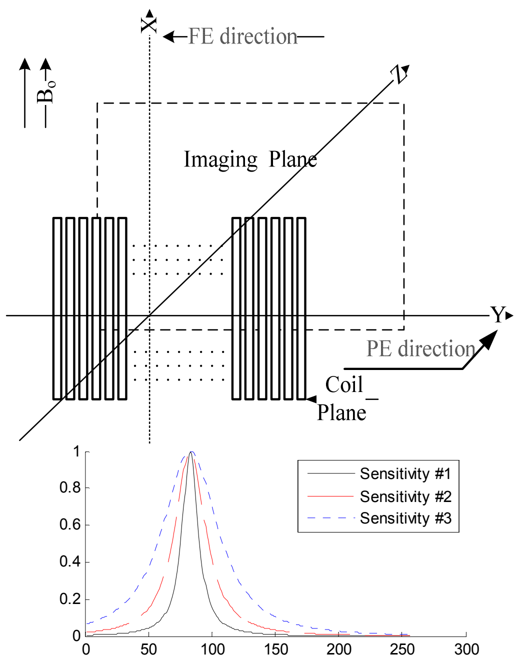


Fig.2 Illustration (a) coil and imaging plane and (b) simulated coil sensitivity profile at three different depths

In this simulation, resolution of sensitivity and the Shepp-Logan phantom was 256*256. White Gaussian noise was added to k-space data and the SNR was 20dB. 32 central PE lines are kept fully sampled as ACS. Aliased individual channel images of each channel were obtained directly by applying inverse Fourier transform of sub-sampled k-space data.

Correlation coefficients matrix of aliased channel images using data generated from sensitivity #1 was shown in Fig.3. Inaccurate correlation estimated caused by aliasing was small.

One set of simulation results was shown in Fig.4. Reconstructions and errors using different channel reduction N_c were provided. A correlation threshold of 0.9 was used for channel reduction and 5 channels were kept. As shown in Fig.4 (b), reconstruction error cannot be further suppressed by increasing channels more than 5. A proper threshold depends on the SNR of acquired data and usually can be set to a smaller to ensure lowest reconstruction error being achieved.

Two sets of in vivo fully sampled data with different array configuration were tested. One set was acquired from a 64-channel linear array and the other from an 8-channel circular array. The channel sensitivity of 64-ch linear array was also localized, thus channel reduction to a small number could be achieved. Reconstructions were shown in Fig.5 (a), no obvious reconstruction difference can be observed

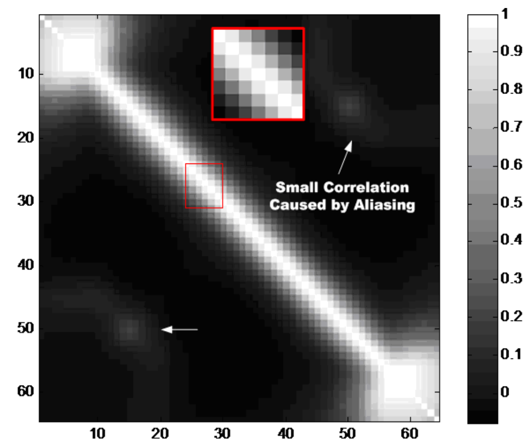
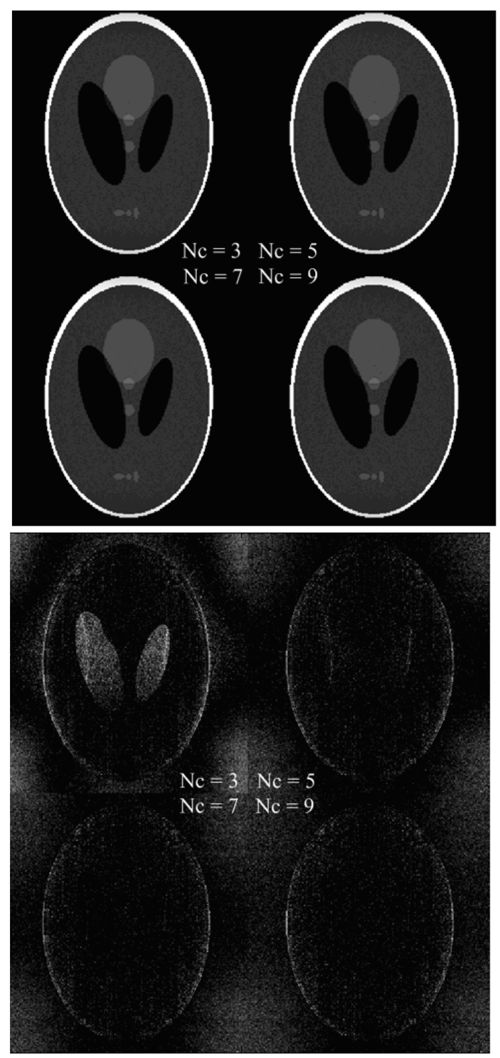


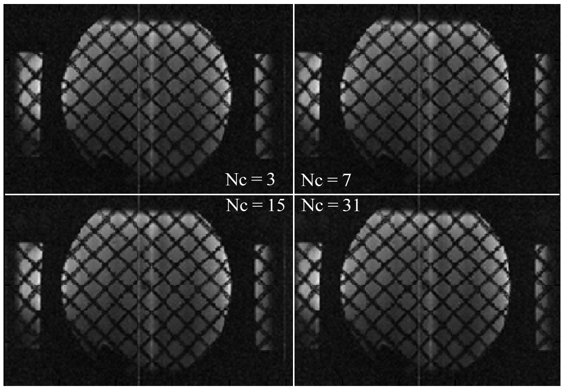
Fig.3 Correlation coefficient matrix of a 64-ch receive system. Note that significant correlation exists only between close neighbor channels (5-7 in this example).



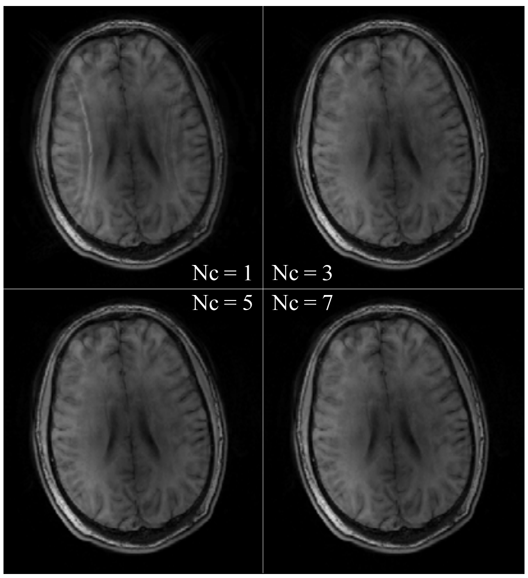
(a)

(b)

Fig.4 Reconstructions from simulated data using MCMLI with 32 ACS lines, 2 blocks and 3 columns with four different neighboring channels (3, 7, 15, and 31), Rr = 2. (a) Reconstructions. (b) Error images



(a) Real data acquired using a 64-ch linear array receiver system.



(b) Real data acquired using an 8-ch circular array receiver system.

Fig.5 Reconstructions of real data acquired from two different array configurations. Both data sets were down sampled at Rr=2 and reconstructed using different channel reductions. No significant decrease of reconstruction quality was observed for more channel

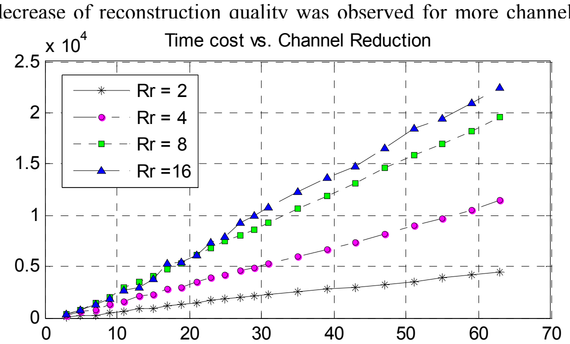


Fig.6 Time cost of reconstruction of 64-ch real data versus channel reduction at different reduction factors. Time cost is proportional to the number of channels adopted in reconstruction.

between N_c=3 and N_c=31. Reconstructions of data acquired from a circular array were shown in Fig.5 (b), only the single channel reconstruction N_c=1 had obvious aliasing effect. As long as some channel members are low correlated in array, channel reduction can be applied for many array configurations.

IV. Conclusion

A method to significantly reduce the computation burden in the k-domain parallel imaging with large receive arrays was presented. By utilizing localized sensitivity, the method adaptively selects a small set of neighbor channels in the GRAPPA/MCMLI interpolation models for each individual channel. In the simulated and in-vivo experiments, significant computation saving was obtained with minimal reduction of reconstruction quality.

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