Correlation-based reconstruction for parallel imaging

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Introduction: It is well known in MRI that coil array design poses a physical limit to parallel imaging acceleration because reconstruction from undersampled data relies on the data relationship introduced by multi-channel coil sensitivities [1-3]. The work presented here aims to develop a new reconstruction framework to overcome this limit by taking advantage of all available data relationships in parallel acquisition. In this new framework, which we call "correlation-based reconstruction", correlation functions are used to mathematically describe a generic data relationship, and the reconstruction relies on the estimation of correlation functions from prior knowledge about imaging data. In a high-resolution brain imaging experiment using an 8-channel head coil array with at most 4 elements in any physical direction, it is demonstrated that a conventional parallel imaging technique performs well only if an acceleration factor ≤ 4 is used, while the correlation-based reconstruction provides excellent image quality even with an acceleration factor far beyond that limit.

Theory: The data relationship of two sets of k-space imaging data $s_1(k)$ and $s_2(k)$ can be described mathematically using a correlation function [4] given by:

$$C_{s_1 s_2}(k) = \sum_{k'} s_1(k')\cdot conjugate\{s_2(k'+k)\} \qquad (1).$$

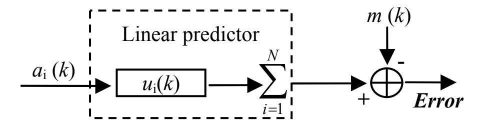

Fig. 1. Linear prediction model for parallel imaging reconstruction. i: channel index; $a_i(k)$: acquired data; m(k): real data; $u_i(k)$: linear filters for prediction.

This mathematical depiction is useful when seeking a solution to the linear predication model [4] shown in Fig. 1. This model describes parallel imaging reconstruction, if $\{a_i(k),\ i=1,2,\ldots,N\}$ represents the undersampled data acquired from an N channel coil array, the linear predictor $\{u_i(k),\ i=1, 2, \ldots, N\}$ represents the reconstruction in k-space, and $m(k)$ represents the real image data. To minimize the sum of squares error in reconstruction, a solution to the linear predictor can be obtained from a set of linear equations given by:

$$\sum_{i=1}^{N}\left[C_{a_i a_j}(k)\right]\otimes u_i(k) = C_{ma_j}(k),\ j=1,2,...,N \qquad (2),$$

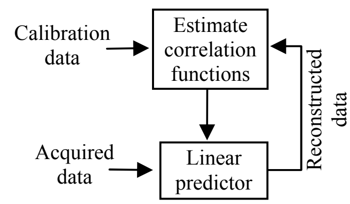

Fig. 2 Illustration of the framework of correlation-based reconstruction.

where ⊗ represents convolution. It should be noted that the coefficients of the linear equations are determined by the correlation functions (defined by Eq. 1) of acquired data and real data, implying the reconstruction may take advantage of every data relationship that can be mathematically represented by a correlation function. This allows for the use of all available data information in parallel imaging to optimize the reconstruction. Fig. 2 shows the overall framework of correlation-based reconstruction. It can be seen that the reconstruction is iterative: The algorithm is initiated by the estimate of correlation functions from calibration data. The correlation functions are iteratively updated by the calibration data and the data reconstructed from the acquired data using the linear predictor. In this work, we used three data relationships for correlation-based reconstruction: 1) neighboring k-space data relationship introduced by coil sensitivities, 2) data correlation between k-space data and their conjugate symmetric data, and 3) data consistency from center and outer k-space data. The first relationship has been used in conventional parallel imaging [1-3]. The second relationship has been used in partial Fourier imaging and recently in parallel imaging [5]. The third relationship arises from the intrinsic correlation from low- to high-resolution data in a medical image.

Methods and Materials: A brain imaging experiment was conducted using a standard 8-channel head coil array (Invivo Corporation, Gainesville, Florida) on a 3T clinical MRI scanner. Axial image data were acquired with full Fourier encoding using a T_1 FLAIR sequence (FOV 220×220 mm, matrix 512×512, TR/TE 3060/126 ms, flip angle 90°, slice thickness 5 mm). The phase encoding direction was left-right. The data for parallel imaging reconstruction were generated by undersampling the fully sampled data with a series of reduction factors, R=2, 3,…, 8. The calibration data were 24 center k-space lines. A standard GRAPPA algorithm was used as a reference for reconstruction. Correlation-based reconstruction (2 iterations) from the same set of data was compared with GRAPPA.

Results: It should be known that the head coil array used in this work has eight elements uniformly placed around the head anatomy and the number of elements in any direction is at most 4. As a result, the imaging acceleration using a conventional parallel imaging technique is limited by this factor due to its complete dependence on coil sensitivities. In Fig. 3, it can be seen that GRAPPA performs well when R≤ 4. However, this conventional reconstruction technique gives strong aliasing artifacts when R>4 indicating the spatial encoding of coil sensitivities is not sufficient. Compared with GRAPPA, correlation-based reconstruction performs very well with all reduction factors from 2 to 8, indicating this framework offers imaging acceleration capability beyond the limit posed by the coil array. This improved parallel imaging performance can also be seen quantitatively from the calculated Root-Mean-Squared Errors (RMSE) shown in Fig. 3.

Conclusion: By taking advantage of all available data relationships, correlation-based reconstruction offers the capability of parallel imaging with a reduction factor higher than the limit posed by coil array in conventional parallel imaging.

Reference: [1]. Sodickson, D.K. et al., MRM 1997, 38: 591-603. [2]. Prussmann, K.P. et al., MRM 1999, 42: 952-962. [3]. Griswold, M. A. et al., MRM 2002, 47:1202-1210. [4]. Hayes M. Statistical digital signal processing and modeling. New York: John Wiley & Sons, Inc; 1996. [5]. Blaimer, M. et. al., MRM 2009, 61:93-102.

Fig. 3 Comparison of parallel imaging performance between GRAPPA and correlation-based reconstruction in high-resolution brain imaging. (a) Reference image from fully sampled data. (b) Reconstructed images using GRAPPA (top row) and correlation-based reconstruction (bottom row) with reduction factors R=2, 3, …, 8. The percentage numbers are RMSEs relative to the reference image.