Simultaneous Calibration Scheme for Data-Driven Parallel Imaging Reconstruction

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Introduction: Autocalibrating parallel imaging methods, e.g. GRAPPA [1] or ARC [2], demonstrate good reconstruction quality even in challenging imaging situations. Unlike SENSE [3], these methods do not require explicit coil sensitivity maps but rather use a data fitting approach to calculate the linear combination weights that synthesize output data from input data. We refer to this class of methods as "data-driven" because they are based on a limited knowledge of the underlying physical process and rely on training data to calibrate the relationship between input and output data.

Autocalibrated training data collected within a given scan may often be limited in quality or quantity, for example, due to motion, pulse sequence, or scan time requirements. In these cases, it could be beneficial to use external training data from another scan. It has previously been shown that weights derived from calibration data acquired with one type of SNR and image contrast can be used to unalias data acquired with another type of SNR and image contrast [4]. In this work, we demonstrate a modified calibration strategy for data-driven reconstruction whereby multiple datasets with different magnetization can be used *simultaneously* to train the reconstruction.

Theory: Data-driven parallel imaging reconstruction can be expressed in the form $\mathbf{d}_{syn}= \mathbf{D}_{acq}\mathbf{w}$, where $\mathbf{d}_{syn}$ contains single-coil data synthesized by linearly combining multi-coil acquired data in $\mathbf{D}_{acq}$. The weights $\mathbf{w}$ are derived during a calibration phase by solving $\min_{\mathbf{w}} \left\| \mathbf{D}_{src}\mathbf{w} - \mathbf{d}_{tgt} \right\|$, where $\mathbf{D}_{src}$ and $\mathbf{d}_{tgt}$ are comprised of source and target data, respectively, from a fully sampled calibration region. Each row of $\mathbf{D}_{src}$ and $\mathbf{d}_{tgt}$ represents a training example for the reconstruction. A sufficiently large number of training examples are typically acquired such that the system is highly overdetermined, and weights can be found to minimize the error in the fit between source and target data over all training examples.

The goal of this work is to calculate reconstruction weights $\mathbf{w}$ that satisfy more than one set of calibration data, where the datasets may have different underlying magnetization (e.g. image contrast, phase, SNR, etc) but share the same coil setup and field-of-view. Simultaneous calibration can be achieved by calculating weights that minimize the fit error over all N calibration datasets, as follows:

$$\min_{\mathbf{w}} \left\{ \alpha_1 \left\| \mathbf{D}_{src(1)}\mathbf{w} - \mathbf{d}_{tgt(1)} \right\| + \alpha_2 \left\| \mathbf{D}_{src(2)}\mathbf{w} - \mathbf{d}_{tgt(2)} \right\| + \cdots + \alpha_N \left\| \mathbf{D}_{src(N)}\mathbf{w} - \mathbf{d}_{tgt(N)} \right\| \right\},$$

where $\mathbf{D}_{src(n)}$ and $\mathbf{d}_{tgt(n)}$ represent training examples from dataset n. The α terms are used to control the relative importance of each dataset, e.g. if α_1=1 and all other α_n=0 (n=2…N), then only dataset 1 is used for calibration; if α_n=1/N (n=1…N), all datasets are treated with equal importance. This equation can be rewritten:

$$\min_{\mathbf{w}} \left\| \begin{bmatrix} \alpha_1 \mathbf{D}_{src(1)} \\ \alpha_2 \mathbf{D}_{src(2)} \\ \vdots \\ \alpha_N \mathbf{D}_{src(N)} \end{bmatrix} \mathbf{w} - \begin{bmatrix} \alpha_1 \mathbf{d}_{tgt(1)} \\ \alpha_2 \mathbf{d}_{tgt(2)} \\ \vdots \\ \alpha_N \mathbf{d}_{tgt(N)} \end{bmatrix} \right\| \equiv \min_{\mathbf{w}} \left\| \tilde{\mathbf{D}}_{src}\mathbf{w} - \tilde{\mathbf{d}}_{tgt} \right\|,$$

where $\tilde{\mathbf{D}}_{src}$ and $\tilde{\mathbf{d}}_{tgt}$ are defined as expanded source and target matrices obtained by vertically concatenating N sets of α_n-weighted calibration data. The weights can then be calculated: $\mathbf{w} = \tilde{\mathbf{D}}_{src}^{+}\tilde{\mathbf{d}}_{tgt}$ ($^{+}$ denotes pseudoinverse).

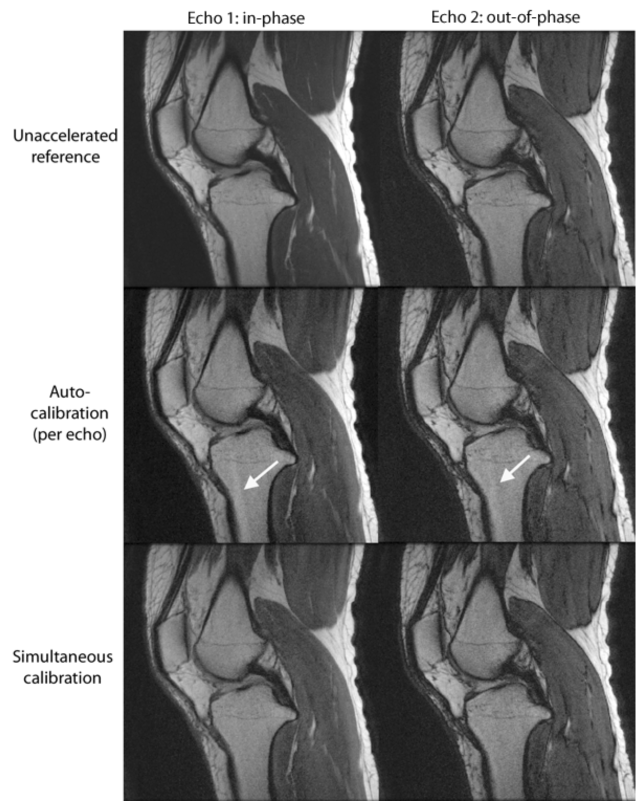

Figure 1. Residual aliasing artifacts visible using per-echo autocalibration (arrows) are removed when calibration is performed over both datasets simultaneously.

Methods: To demonstrate one possible application of simultaneous calibration, volunteer knee imaging was performed at 1.5T (Signa HDx, GE Healthcare, Waukesha, WI) using an 8-channel knee coil. Fully sampled data were acquired using a multi-echo fast spin echo sequence modified to acquire 2 interleaved datasets with water and fat in-phase and out-of-phase. First, unaccelerated images were reconstructed as a reference case. Data were then accelerated offline by 2x and each echo included a central calibration region spanning only 7 lines. Accelerated images for each echo were reconstructed using two variations of ARC reconstruction: 1) autocalibration on each echo separately; and 2) simultaneous calibration, where data from both the in-phase and out-of-phase datasets were used with α_n*=0.5*. In both cases, a 3x7 reconstruction kernel was used.

Results: Figure 1 compares fully sampled data (row 1) with accelerated data reconstructed using per-echo autocalibration (row 2) and simultaneous calibration (row 3). A prominent residual aliasing artifact of the posterior subcutaneous fat is visible in the autocalibrated images (arrows) due to the insufficient amount of calibration data available within each echo. When simultaneous calibration is used to incorporate training examples from both datasets, reconstructed image quality is considerably improved, even though the datasets have different image contrast and phase.

Discussion: This work demonstrates the technical feasibility of simultaneous calibration for data-driven reconstruction. By exploiting calibration data from multiple unique data sets, this method can allow improved weight calculation when calibration data is otherwise limited. While methods like TSENSE [5] reduce calibration burden by using time-interleaved phase-encoding, such methods are incompatible with datasets whose magnetization varies significantly, as changes in signal or phase between datasets may be misinterpreted as coil sensitivity variation and cause artifacts. Simultaneous calibration could help to reduce the calibration burden in time-limited applications where magnetization changes appreciably.

References: [1] Griswold et al. 2004 MRM 52:1118-26. [2] Beatty et al. ISMRM 2007, 1749. [3] Pruessmann et al. 1999 MRM 46:638-51. [4] Griswold et al. 2006 NMR in Biomedicine 19:316-24. [5] Kellman et al. 2001; MRM 45:846-52.