INTRODUCTION:
Parallel imaging is increasingly used in the clinical MRI setting. A variety of different reconstruction approaches were proposed (1,2,3) that either work in k-space or image domain. The problem of B0 artifacts in parallel imaging however is not settled, since ‘B0-encoding’ does not happen in either k- or image space but simultaneously in both. This is why a concatenation of unaliasing and traditional B0-reconstruction fails and a simultaneous reconstruction must be conceived. In the present work the generalization of an iterative B0-reconstructed reconstruction (4) toward parallel imaging is described and in-vivo results are presented.

THEORY AND METHODS:
At the reconstruction level, the problem of B0 inhomogeneity is typically addressed by unwarping (5) or conjugate phase reconstruction (6,7,8). However, the conjugate phase approach relies on the assumption that B0 varies smoothly in space. Recently, iterative solutions were suggested which can cope with strongly varying B0 (4, 9).

The problem of compensating for in-plane B0 inhomogeneity in the reconstruction is frequently badly conditioned, leading to numerical instability and local noise enhancement. To address this problem, it has been proposed (4) to minimize the weighted sum of the noise variance and the expected squared signal error on a pixel-by-pixel basis. This is achieved with the reconstruction formula:

\[ \mathbf{I} = \mathbf{B} \mathbf{E} \mathbf{H} \mathbf{I} + \alpha \mathbf{X} + \beta \mathbf{E} \mathbf{H} \mathbf{I}^\dagger \mathbf{E} \mathbf{H} \mathbf{I} + \mathbf{m} \]

where \( \mathbf{m} \) is a vector of multiple-coil k-space data, \( \mathbf{I} \) the vector of the reconstructed pixel values, \( \mathbf{E} \) the encoding matrix and \( \mathbf{E}^\dagger \) its Hermitian adjoint. The superscript + denotes the Moore-Penrose pseudoinverse. \( \alpha \) and \( \beta \) are coefficients representing the weight of noise and signal variance, respectively, in the joint minimization. \( \mathbf{Y} \) denotes the noise covariance of the sample values and \( \mathbf{X} \) the signal covariance, which represents potential prior knowledge about the signal distribution in the object. Note that the set of target pixel positions can be arbitrarily large, corresponding to an arbitrary target image matrix. For the particular case of sensitivity- and Fourier encoding under the influence of B0 inhomogeneity, the encoding matrix reads

\[ \mathbf{E} \mathbf{r}_p \mathbf{X} = s \mathbf{r}_p \exp(i \mathbf{k} \mathbf{r}_p - \mathbf{q}_0 \mathbf{r}_p), \]

where \( \mathbf{k}_p \) and \( \mathbf{r}_p \) denote the \( p \)-th sampling position in k-space and the position of the \( p \)-th pixel in the image domain, respectively. \( \mathbf{q}_0 \) denotes the B0-induced frequency offset at the position \( \mathbf{r}_p \), and \( \mathbf{t}_p \) denotes the time at which the sample \( \mathbf{x} \) is taken. The sensitivity of coil \( \gamma \) at position \( \mathbf{r}_p \) is given by \( s \mathbf{r}_p \). For image reconstruction with Eq. (1), the matrix inversion part is solved by the CG method. Its solution \( \mathbf{c} \) can then be pre-multiplied by the left-most part of Eq. (1) to get the reconstructed image:

\[ \mathbf{I} = \mathbf{B} \mathbf{E} \mathbf{H} \mathbf{I} + \alpha \mathbf{X} + \beta \mathbf{E} \mathbf{H} \mathbf{I}^\dagger \mathbf{E} \mathbf{H} \mathbf{I} + \mathbf{m} \]

The efficiency of each loop in the CG scheme (Fig.2) can be enhanced considerably by performing the matrix-vector multiplications with \( \mathbf{E} \mathbf{H} \mathbf{I} \) combined by multiquadric interpolation (MFI) (8) with fast Fourier transform, in a scheme related to an approach proposed in Ref. (10) (Figs.1 and 2).

Fig. 1: In the MFI the k-space data is demodulated at L different frequencies (Demod), inverse Fourier transformed and multiplied by the corresponding coefficient maps \( \mathbf{C} \) before being summed up. Gridding is not shown but can readily be incorporated.

RESULTS:
The measured data was reconstructed using standard DFT reconstruction, conventional MFI, and the proposed reconstruction (30 iterations, reconstructed on a 512x512 grid, 2 hours computation on a 2.8 GHz CPU). MFI recovers the original residual, multiplied by \( \mathbf{m} \), added for regularization.

DISCUSSION AND CONCLUSION:
The proposed method permits simultaneous correction of B0-corrupted SENSE data without restrictions in terms of local B0 variation. The reconstruction scheme is readily applicable to fMRI data if the k-space trajectory is accurately known, suggesting promising applications in fMRI and DTI. The reconstruction scheme is readily applicable to general k-space trajectories, suggesting promising applications in fMRI and DTI. Ultimately, the reconstruction is limited by the inherent information content of the acquired data. Excessive field inhomogeneity will cause deteriorating conditionings, shifting the balance in the weighted minimization toward unfavorable compromises of the spatial response. Potential means of working against this problem are fast, non-Cartesian sampling patterns.

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