A Combination of Nonconvex Compressed Sensing and GRAPPA (CS-GRAPPA)

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Introduction

Compressed Sensing (CS) (e.g. [1]) is a novel approach to reconstruct sparse undersampled datasets. Several papers (e.g. [2]) have demonstrated the benefit of CS in the field of MRI. Nonconvex CS [3] is a more recent development which allows for even higher acceleration factors and is easy to implement. A first application for dynamic cardiac imaging has been demonstrated [4]. However, these CS approaches do not take advantage of the inherent coil sensitivity information in multi-channel datasets. First formulations of CS algorithms utilizing the SENSE [5] formalism which take advantage of the coil sensitivity information in the reconstruction process have been presented (e.g. [6]). It could be shown that a combination of CS and Parallel Imaging allows for higher acceleration factors than each individual method. This work demonstrates an extension of the nonconvex CS approach from [3,4] which introduces a GRAPPA [7] reconstruction step. The advantages of this technique are that no coil sensitivity scan is necessary, and the algorithm does not need any optimized parameters to converge to the correct solution.

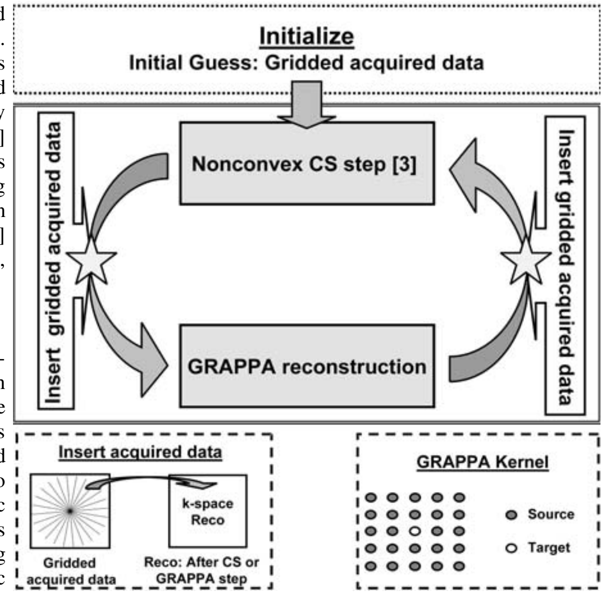

Figure 1: Schematic of the CS-GRAPPA algorithm.

Materials and methods

We propose to add a GRAPPA reconstruction step for every point of the dataset after the coil-by-coil CS reconstruction step; this introduces a coil sensitivity constraint to the algorithm which ensures that the reconstructed data are in accordance with the inherent coil sensitivity profiles. The GRAPPA step uses a 5x5 kernel with the central point removed (see Fig. 1). This approach is similar to the iterative GRAPPA approach [8], but this work includes a CS step and is simplified (e.g. no resampling necessary). The new extended algorithm based on [3] is outlined in Fig. 1. To demonstrate the potential of this algorithm in the dynamic MRI context, a radial dynamic cardiac dataset with 32 coils, 21 timeframes, 192 readout points and 224 projections per timeframe was acquired. After subtracting the undersampled timeframe projections from the corresponding projections of the composite image (temporal average of dataset) which leads to sparse dynamic difference images [4], the data were gridded using GROG [9]. In the next step, the dynamics were reconstructed using

- the original nonconvex algorithm applied
  - after adaptively combining the individual coils [10] (discard GRAPPA step in Fig. 1 and combine coils before CS reconstruction)
  - to each individual coil (discard GRAPPA step in Fig. 1)
- the proposed CS-GRAPPA method.

The final timeframe image is obtained by subtracting the reconstructed sparse differences from the composite image. 16 interleaved projections out of 224 were used for reconstruction.

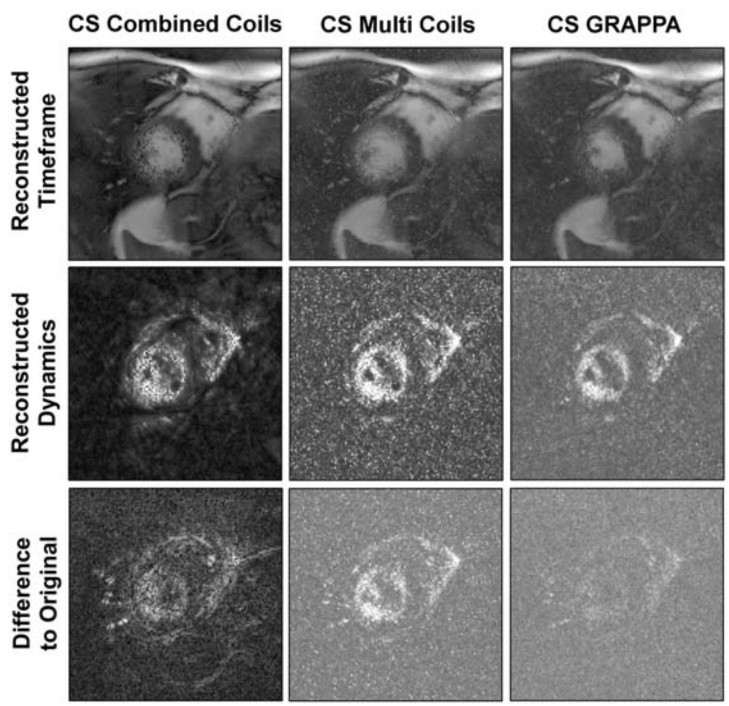

Figure 2: Reconstruction results. 16 out of 224 projections were used. The difference images are multiplied by a factor of 4

Results

The CS reconstruction on datasets with combined coils (CS Combined Coils, Fig. 2) exhibits noise-like artefacts, and the border between myocardium and ventricle is severely obscured. When reconstructing each individual coil with CS (CS Multi Coil), the myocardium border is even more blurred and barely visible at the expected position. However, the CS-GRAPPA reconstruction offers a significantly lower artefact level and a clear myocardium-ventricle distinction. The differences between the CS-GRAPPA reconstruction and the original timeframe are close to the noise-level while both CS reconstructions without the additional GRAPPA step exhibit structural differences.

Discussion

The GRAPPA step introduces a new constraint to the CS algorithm: Besides data consistency, the reconstructed data must correspond with the inherent coil sensitivity profiles. Furthermore, it is possible to improve the image fidelity by using a GRAPPA kernel on each CS reconstructed k-space point by exploiting the information provided by the coil sensitivity profiles. This leads to a dramatic increase in reconstruction quality from highly undersampled datasets compared to previously published results [4]. Since one can access the acceleration potential of CS and GRAPPA simultaneously, the presented work shows promise for all applications where high spatial and high temporal resolution are required.

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