Automatic Time Frames Subset Selection for Improved TGRAPPA Reconstruction

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Introduction

In TGRAPPA (1), several adjacent undersampled time frames are combined to form the data used for calibration in the GRAPPA reconstruction process. However, how to choose the optimal number of time frames that balances between artifacts and signal-to-noise ratio (SNR) for a given dynamic data set has not been investigated. In this work, we present a method that exploits the shift invariance property of Cartesian GRAPPA (2) to select the number of time frames for an optimal TGRAPPA reconstruction.

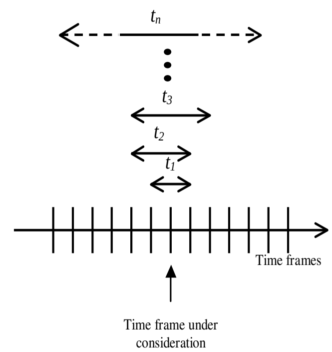

Fig. 1 formation of the set of time frames to be

Materials and methods

Experiments were performed on a 1.5T Siemens Avanto whole-body MR scanner (Siemens Medical Solutions, Malvern, PA) using an 8-channel cardiac coil combined with a 4-channel spine coil for reception and the body coil for transmission. Fully sampled short-axis view real-time non-gated non-breath-hold cardiac data were acquired on healthy subjects using a trueFISP sequence and later downsampled as described in (1) with acceleration factor of 3 for emulating parallel imaging data.

In GRAPPA, the skipped lines are filled by interpolation using weights derived during calibration. Since GRAPPA kernel should be shift invariant in the k-space, the filled lines can also be used to predict the acquired lines, providing a measure to evaluate the accuracy of the weights in the form of the mean square difference between the acquired lines (A) and the estimated acquired lines ($\tilde{A}$). In TGRAPPA, adjacent undersampled time frames are assembled to provide data for deriving the weights used for reconstruction. Therefore, a set of time frames t_n that results in an optimal reconstruction is assumed to minimize the cost function given by.

$$\Psi(t_n) = \left\|\tilde{A}(t_n) - A\right\|^2$$

While this is a general approach permitting the selection of any set of time frames, for simplicity, we assume that the optimal set comprises of consecutive frames nearest the estimation location. For a given undersampled frame to be reconstructed, we therefore started our examination with the minimum number of adjacent time frames necessary to form a complete data set for calibration, which equals the parallel imaging acceleration factor (including the time frame under consideration). Then we formed other sets of time frames to be examined by adding one time frame at the time as pictured in Fig. 1, up to 27 frames. The set of time frames that gives the minimum cost function is then used for the GRAPPA reconstruction for the given frame. The effectiveness of the method is demonstrated with *in vivo* data and its performance is compared with the conventional TGRAPPA reconstruction as described in (1).

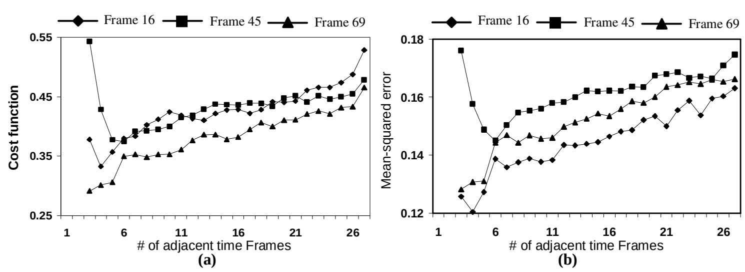

Fig. 2. (a) Cost function and (b) Mean-squared errors evaluated from different numbers of frames

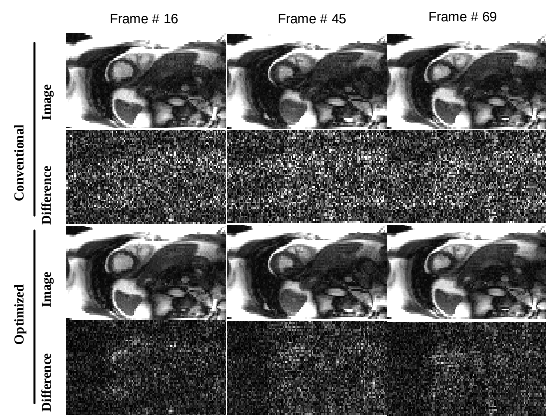

Fig. 3. Comparison of reconstruction results between the conventional TGRAPPA and proposed TRGAPPA

Results and Discussion

Fig. 2 shows the cost function (CF) (a) and the mean-squared error (MSE) derived by comparison with images reconstructed from fully sampled data (b), for three different time frames, plotted against the number of adjacent time frames used for calibration, ranging from 3 to 27. The minimum for the 3 frames occur at 3, 4, and 6 respectively. The good correspondence between our CF and the MSE demonstrates the validity of using CF as a measure to identify the optimal number of time frames for calibration. Fig. 3 shows images generated using the number of time frames that minimizes CF in Fig. 2 and compared to the reconstruct results using the conventional TGRAPPA algorithm. The difference images shown in each case is the absolute difference between the fully sampled image (not shown) and the reconstructed image. As indicated by the difference images, conventional TGRAPPA results in more noise/error in the image, and this noise/error is significantly reduced with the new approach described here. Fig. 4 shows the plots of the reconstruction errors, which are the sum of square of the difference images, versus the frame number, demonstrating the improved performance of the new method over the conventional TGRAPPA.

Although in general the optimal set of frames may not need to contain only consecutive neighbors of the frame to be reconstructed, our simplified approach of using only neighboring frames led to decent results. The cost function introduced in this work provides a general framework for model selection in GRAPPA based reconstruction. It can be easily extended to the selection of optimal kernel for any GRAPPA related reconstruction algorithms and therefore can constitute a valuable alternative to the method described in (3).

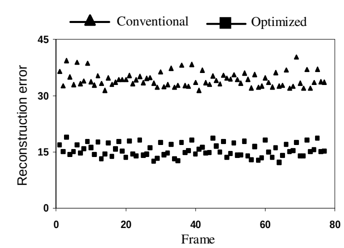

Fig. 4. Comparison between errors

Conclusion

A method that exploits the shift invariance property of Cartesian GRAPPA is introduced for optimal time frames subset selection in TGRAPPA reconstruction. This data-driven approach was proven with experimental data to lead to improved performance. Because the method is simple and is applied in post-processing, it can be used with TGRAPPA routinely

Reference:

1. Felix A. Breuer *et al.,* MRM 2005; 53(6): 981-985. 3. Mark A. Griswold, *et al*., 2005;54(6):1553-1556 3. R. Nana *et al.*, ISMRM 2007 ; p 747

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