Automatic Coil Selection for SENSE Imaging with Large Coil Arrays

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Introduction

Parallel imaging using coil arrays with large number of receive elements allows improved imaging performance and increased SNR [1, 2]. However, the use of a large number of coil elements can lead to memory storage problems and to increased reconstruction times. Several techniques for data reduction were presented, realized either by linear combination of the original coil data or by discarding particular data from unimportant coils elements [3-5]. In this work, we focus on coil selection and present an efficient approach applicable to massively parallel SENSE imaging.

Methods

An appropriate criterion for a coil subset selection should refer to the image quality if an image is acquired with a given coil configuration. One such quality measure is the signal-to-noise-ratio (SNR). The SNR in parallel imaging is spatially variable, so local SNR optimization will lead to a different coil configuration for each pixel. A more global quality characteristic is the mean SNR. The optimal coil set can be found by performing an exhaustive search through all possible coil subsets and selecting the set with highest mean SNR, but the number of possible coil combinations makes this problem computationally challenging.

The SENSE reconstruction of uniformly undersampled Cartesian data consists of solving a linear system of L equations with R variables, where L is the number of coil elements and R is the reduction factor. The reconstruction problem could be solved by means of singular value decomposition (SVD). The data **a** and the sensitivity **S** are projected from the L to an R dimensional space $\mathbf{a'} = \mathbf{Pa}$, $\mathbf{S'} = \mathbf{PS}$ and the problem is solved in this lower dimensional space. The projection matrix can be given as $\mathbf{P} = \mathbf{U}^{\mathbf{H}}$, where **U** comes from the SVD of the sensitivity matrix $\mathbf{S} = \mathbf{U\Sigma V}^{\mathbf{H}}$. The coil sensitivities in the R-dimensional space can be considered as coil sensitivities of R virtual coils [6]. If the best subset of a given coil set has to be selected, the upper SNR limit would be given by the full coil set. So, finding those coils that have the most similar projection on the R-dimensional problem space to the projection of the full coil set will result in an optimal SNR coil configuration. The i-th row vector of **S'** can be written as a linear combination of the rows of **S**

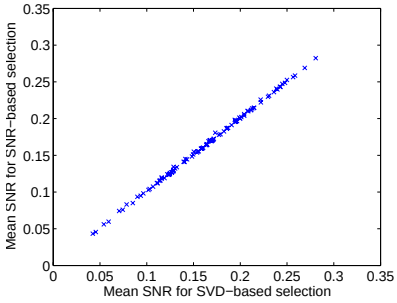

Fig.1 Comparison between SVD-based and SNR-based coil selection (16 out of 32). The mean normalized SNR for the 100 different coil configurations selected by both approaches shows their good correlation.

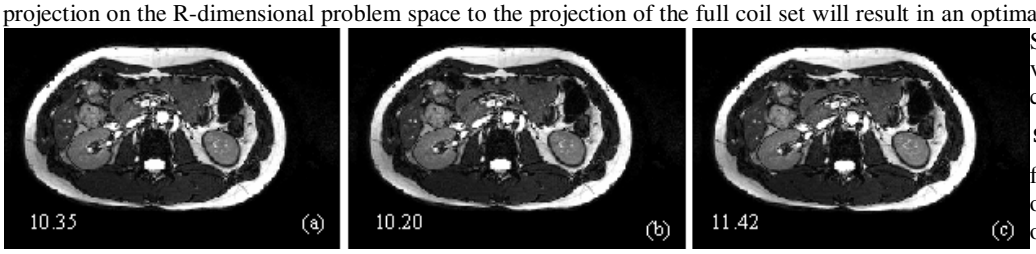

Fig.2 In vivo experiments. Images, reconstructed with (a) 16 coils chosen out of 32 with the SNR-based coil selection algorithm, (b) 16 coils chosen with the SVD-based coil selection algorithm, (c) the full set of 32 coil elements The mean normalized SNR values are given on the lower left of each image.

$\mathbf{s_i'} = \sum_{\mathbf{k}} \mathbf{p_{ik}} \mathbf{s_k}$, where the weighting factors $\mathbf{P(i,k)} = \mathbf{p_{ik}}$ are the i-th row entries of the projection matrix **P**. The magnitude of $\mathbf{p_{ik}}$ represents the contribution of the k-th physical coil to the i-th virtual coil. The coil array elements can be ranked according to the weighting function:

$$\mathbf{W_k} = \sum_{\mathbf{r} \in \mathbf{ROI}} \sum_{\mathbf{i}} |\mathbf{p_{ik}}|$$

This allows a single step coil selection using the SVD of the sensitivity matrix, which we will denote as the SVD-based coil selection.

To validate the performance of the method, it should be compared with the results of the exhaustive search. However, the number of possible coil combinations makes this task impossible. A faster search using a sequential backward elimination [7] allows the selection in manageable times. We will denote this algorithm as the SNR-based coil selection method and will use it as a reference.

Results and Discussion

To evaluate the performance of the SVD-based coil selection, simulations with 100 different coil arrays selecting 16 out of 32 coil elements have been performed, which are summarized in Fig 1. A very nice correlation with the SNR-based coil selection is shown. The SVD-based coil selection algorithm was further demonstrated for in-vivo measurements for the selection of 16 out of 32 coil elements. All measurements were performed on a 1.5T clinical scanner (Philips Medical Systems) equipped with a 32-element coil array. 2D in-vivo images were acquired with SENSE (R=2) in AP (TE = 1.5 ms, TR = 3 ms, balanced FFE, $\alpha = 60^{\circ}$, FOV = 410×410 mm^2, matrix size 288×288 and slice thickness 7 mm). Fig.2 (a), (b) show the images obtained with 16 coils selected with the SNR-based and SVD-based coil selection algorithms, respectively. Both algorithms resulted in similar coil selection pattern, and the resulting images show only small decrease in SNR compared with the image obtained with the full set of 32 coils (Fig. 2 (c)). The computation time for the SVD-based algorithm was t_{svd} = 0.02s and for the SNR-based coil selection t_{snr} = 160 s (Xeon, cpu 2,4 GHz, 4GByte memory), which underlines the applicability of the SVD-based coil selection in clinical practice.

Conclusion

The SVD-based coil selection algorithm allows fast coil selection with a performance, comparable with the more accurate, but computationally intensive SNR-based coil selection. It can be used instead of manual coil selection in conventional scan planning and is especially useful in planning double oblique SENSE scans. It is also applicable to various applications such as real-time or interventional imaging, where the selection could be performed locally for each slice enabling dynamical coil switch during image acquisition.

References: [1] Pruessmann K. et al. MRM 1999 42:952-962; [2] Sodickson D. et al. MRM 1997 38: 591-603; [3] Reykowski A. et al. ISMRM 2004: 1587 ; [4] Buehrer M. et al. MRM 2007 57: 1131-1139; [5] Mueller S. et al. MRM 2006 56:1156-1162; [6] Ohliger A. et al. MRM 2003 50: 1018-30 [7] Guyon et al. JMLR 2003 3:1157-1182