Coil Selection Optimization using Mean-Field Annealing and its Application to 128-Channel Imaging

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Introduction: In the past few years, MR scanners have witnessed a large growth in number of receiver channels. Several manufacturers are now offering 32-channel scanners and, recently, 128-channel prototype scanners have been introduced. At the same time, reconstruction algorithms for parallel imaging have become increasingly complex, straining computational resources. We previously developed (1) an algorithm to reduce this computational burden by omitting information from physical coils or "virtual coils" (linear combinations of coils) that do not contribute significantly to image SNR in the region of interest (ROI). In this work, we present an efficient method to optimize the coil selection process inspired by research in neural networks and spin glasses (2) and apply these algorithms to 128-channel MRI.

Methods: We have adapted a combinatorial optimization method which we refer to as "mean-field annealing" (MFA) (2) to the problem of selecting the optimal set of coils or coil combinations for a given ROI and degree of acceptable SNR degradation. A more traditional optimization method to address the same problem is simulated annealing (SA) (3,4). Both MFA and SA are optimization techniques inspired by the statistical mechanics of systems with a large number of degrees of freedom and energy landscapes characterized by many local minima (e.g. spin glasses). In such systems steepest-descent algorithms will often stop at a local minimum. SA overcomes this problem by allowing moves that increase the energy of the system with a probability that depends on temperature. An annealing schedule is set up to gradually reduce the temperature and allow convergence towards the global minimum of the energy landscape. For finite annealing schedules no convergence result to the global minimum has been rigorously proven although, experimentally, low-energy solutions can be found, albeit with high computational cost. MFA is based on an analytical approximation to SA that allows the thermal average of the optimization variables to be computed directly (at a given temperature) by solving a simultaneous set of algebraic equations (mean-field equations). An annealing schedule is set up in this case as well to find the lowest energy state, but it can be much coarser than in the SA case.

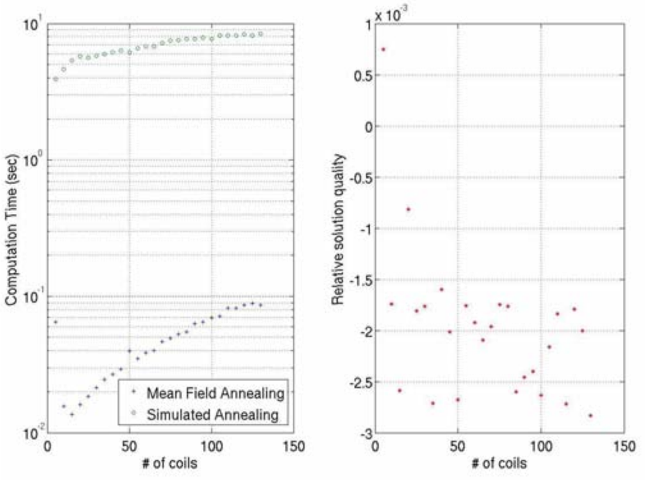

Figure 1. Monte Carlo simulation of solution quality and computation time for MFA and SA vs. number of coils. Relative solution quality = (MFA-SA)/SA.

Results and Discussion: To compare SA to MFA, we ran a Monte Carlo simulation in which we varied the number of coils from 2 to 128. The coil sensitivity functions were assigned randomly and the results averaged over 30 runs. The cost function is given by $-SNR^2$ plus a constraint that selects the number of effective coils to keep. We measured the computation time to find the best solution and the relative solution quality, defined as (MFA-SA)/SA, where MFA and SA are respectively the cost of the best MFA and SA solutions. The results are plotted in Figure 1. We note that MFA is at least a factor of 100 faster than SA over the whole range of coil numbers and that solution quality is only modestly affected (<0.3% worse for MFA relative to SA).

We have tested this algorithm with a 128-channel GE SIGNA prototype scanner. The coil we used is a torso array comprising of two panels (anterior and posterior), with 64 coil elements each (5). We have acquired fully sampled datasets using a partial-Fourier SSFSE pulse sequence (256x160). We undersampled the data offline (R=4) and reconstructed it with a 1D-ASSET homodyne algorithm and with virtual-coil elimination using MATLAB (The Mathworks, Natick, MA). In Figure 2A we show an example of a mid-coronal slice undersampled 4 times in the L/R direction and reconstructed using only 32 virtual coils chosen to optimize SNR at each pixel. MATLAB recon with 32 virtual coils is 2x faster than with 128 (if the arrays can be held in memory, otherwise virtual coils can outperform by a much larger margin). In Figure 2B we show the difference image between Figure 2A and the image reconstructed using all 128 coils. The maximum intensity of both images is clipped at a value of 3. In Figure 3 we show SNR in the three ROIs pictured in Figure 2A as a function of number of virtual coils used in reconstruction.

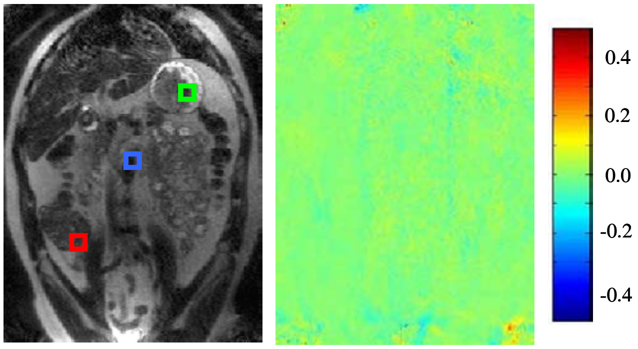

Figure 2. A: Reconstructed image using only 32 out of 128 coils that optimize SNR in ROI. B: Difference image between Figure 2A and image reconstructed with all 128 coils (1D-ASSET homodyne, R=4).

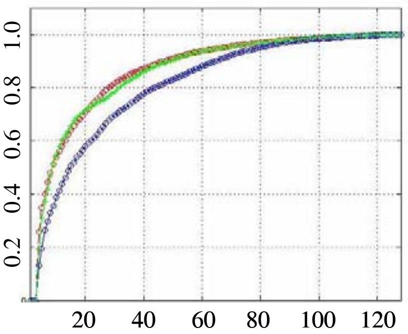

Figure 3 Relative SNR as a function of number of virtual coils used in 1D ASSET Homodyne reconstruction (R=4). Colors correspond to ROIs in Figure 2A.

References: 1, L. Marinelli and C.J. Hardy, Proc. ISMRM 14 (2006), 3659. 2, J.J. Hopfield and D.W. Tank, *Biological Cybernetics* **52**, 141(1985). 3, S. Kirkpatrick et al. *Science* **220**, 671(1983). 4, M. Buehrer et al, Proc. ISMRM 14 (2006), 294. 5, C Hardy et al. Proc ISMRM 15 (2007).