Automated GRAPPA Kernel Selection using Akaike Information Criterion

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Overview. Parallel imaging with multiple receivers is a ubiquitous method in MRI, used both clinically and in basic science research. GRAPPA [1] based reconstructions aim to fill missing k-space data using a local weighted average of neighboring k-space signals acquired by multiple receiver elements. This weighted average can be considered as an estimation model to predict the missing samples at the center of the reconstruction kernel, as shown in Fig.1. The number of parameters in the model is twice the number of points in the kernel times the number of channels. Given a limited set of auto-calibration data the number of parameters in the model can rapidly approach the same order as the number of equations determined by the number of calibration data points. Over-fitting the calibration data makes the result to be sensitive to noise and unstable. At the opposite extreme under-fitting the data also results in poor reconstruction and residual aliasing artifacts [2]. Both issues become more sensitive at high reduction factors and/or with limited reference data. A parsimonious choice of reconstruction kernel would minimize the residual fitting error of the model while simultaneously penalizing over-complex models. This is the rationale behind the Akaiki Information Criteria (AIC), which is a function of the mean squared fitting error, the number of calibration data points, *n* and the number of model parameters, *k* and given by,

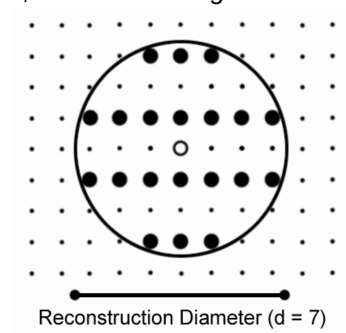

Fig.1

$$AIC = n \ln \sigma_\epsilon^2 + 2k + \frac{2k(k+1)}{n-k-1}.$$

Minimizing this function relative to the kernel support provides an automated approach to kernel selection. While this is a general approach permitting the selection of kernels of any shape, for simplicity, we assume that the optimal kernel prefers points nearest the estimation location and takes the shape of a circle. [3]

Methods. GRAPPA data for R2, R3 and R4 were generated by sub-sampling T1-weighted k-space data (FOV 256 mm, matrix 256) acquired on a 3 Telsa Siemens Trio (Siemens Medical Solutions, Erlangen, Germany) using a product 8 channel head coil assuming a calibration pre-scan of 16 auto-calibration lines. For each reduction factor the kernel diameter was varied from two to sixteen and the AIC was computed for each diameter. The optimal kernel is chosen as the minimum of the AIC curve with respect to kernel diameter.

Results. The computed AIC curves for each reduction factor are shown in Fig. 2. It can be seen that in each case a global minimum is achieved, leading to a kernel diameter of 6.0 for R2, 6.5 for R3 and 8.0 for R4. Reconstructions (R4) based on these choices of kernel diameter and suboptimal choices (d=4.0, d=12.0) are shown in Fig. 3. It is evident that the AIC chosen kernel led to low aliasing and low noise, and provides an excellent compromise between artifact reduction and noise reduction.

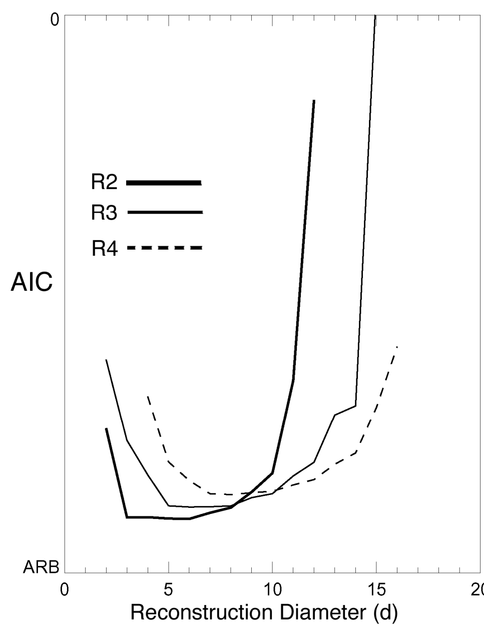

Fig.2

Discussion. GRAPPA reconstructions typically assume a 4x5 kernel approach which may be not optimal in general applications. This paper demonstrates the utility of AIC for automated determination of the GRAPPA kernel size. Rather than an exhaustive search to determine the proper kernel empirically, the present implementation only searches a subset of circular kernels and is therefore computationally efficient. In addition, the AIC curves are convex, so a rapid binary search is possible further minimizing the search time. While only 2D imaging results are demonstrated here, the method is directly extensible to 3D approaches assuming spherical kernels.

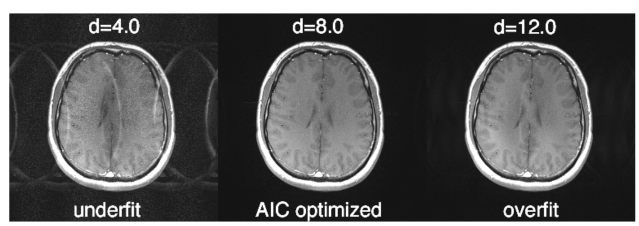

Fig.3

Conclusion. The Akaike Information Criterion provides a robust automatic approach to parallel imaging optimization.

References. 1. Mark A. Griswold et al., MRM 2002; 47:1202-1210. **2.** R. Nana et al., ISMRM 2007; p 747. **3.** Ernest N. Yeh et al., MRM 2005 ; 53 :1383-1392.

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