

Can RF encoding Improve Parallel Imaging?

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Introduction: It is possible to achieve spatial encoding by repeated gradient (Fourier) encoding, using multiple coils (parallel Imaging), or by repeating the acquisition with different RF modulation profiles (RF encoding). Partially Parallel Imaging (PPI) combines Fourier and coil encoding, enabling reconstruction with reduced phase encoding steps but with a signal-to-noise-ratio (SNR) penalty – g-factor (1). Different Fourier encoding schemes have been proposed for PPI. In the Cartesian framework these move from regular sub-sampling (the usual case) to more central weighting where phase encode lines are dense in the centre of k-space and sparser at the edges (2). Kyriakos et al (3) proposed combining PPI with RF encoding (single Hadamard profile shifted in space) to improve reconstructions for defined sampling schemes, particularly centrally-weighted. An improved RF scheme was later proposed for this type of gradient sampling strategy (4). Recent developments in parallel transmit (PTx) make image domain modulations accessible for short RF pulses, renewing interest in this area (5). Here we investigate if previous results (3,4) can be further generalized, asking whether adding RF encoding to PPI can result in a better reconstruction than PPI alone, regardless of the starting Fourier sampling scheme.

Methods: To investigate the interaction of these three spatial encoding methods, a simulation framework and metrics were developed. PPI reconstruction algorithms which do not pose any constraints on the k-space sampling pattern were used. Three methods were investigated: SPACE-RIP (2), generalized-SMASH (6) (or g-SMASH) and generalized-SENSE (7). The condition number of the encoding matrix was used to assess reconstruction quality. Auxiliary simulations confirmed the high degree of correlation ($r^2=0.998$) between the condition number and the mean g-factor (averaged across the whole image). Encoding matrices were built for centrally-weighted, random, and regularly sub-sampled schemes. These were allowed to be modified by adding shot by shot RF modulation. A search algorithm was employed (the MATLAB genetic algorithm function (8)), to determine the set of RF modulation profiles which, when combined with each sampling scheme, would lead to optimal reconstruction (lowest condition number). The optimization was repeated several times with different starting points to avoid local minima. To keep computational times feasible, a 1D problem was formulated (1×16-sized image). A preliminary study was performed to confirm that results previously reported by others (3,4) also hold at this smaller scale. Only the characteristics of the coils and k-space sampling patterns were specified (no object information). A linear array was simulated comprising four coils with Gaussian profiles. The distance between coil elements was fixed (4 pixels), ensuring good coverage of the 16-pixel space. Different coil widths (standard deviations of $\sqrt{2}$ and 2 pixels) and acceleration factors (R=2 and R=4) were considered. Shot by shot RF modulation was simulated via the following rules: the sampled k-space point (and therefore the coil footprint) could be shifted and replicated along the phase encode direction. Up to two replicas were allowed for R=4, and four for R=2. This is equivalent to each RF profile having up to two or four Fourier terms, respectively; the number required for Hadamard encoding in order to distinguish between four (R=4) or eight (R=2) different spatial locations. The phase and amplitudes of the complex weights given to each Fourier term were constrained so that only phase modulations would be obtained in order to avoid loss or unphysical gain of SNR. To evaluate how close, in each case, the RF-modulated matrix was to a standard regular sampling pattern, a quantitative measure of “regularity” (\mathfrak{R}) was devised. Regular sampling corresponds to a more even occupancy of the columns in a g-SMASH matrix. Hence, after taking their magnitude, all the rows corresponding to each coil were added together. The mean row within all coils was calculated, and \mathfrak{R} was then defined as the standard deviation along the phase encode direction. Regular sampling corresponds to lower information overlap and therefore to lower \mathfrak{R} .

Results: For all tested cases the condition number of the encoding matrices was independent of the reconstruction algorithm. Regular sub-sampling resulted in the lowest condition number and was not improved by RF modulation; these also had the lowest \mathfrak{R} (Figure 1, red symbol). Centrally-weighted and randomly sampled (non-regular) cases resulted in larger condition number (less good reconstructions, e.g. blue symbol in Figure 1) regardless of the coil width and reduction factor chosen. In these cases condition number could be reduced through RF encoding, but the optimal results had condition numbers equal to those of the corresponding non-RF-modulated regularly-sampled encoding matrices. In all situations, visual inspection of the RF modulated g-SMASH reconstruction matrices having the lowest condition numbers indicated that they strongly resembled non-modulated regularly-sampled matrices. This was supported by the “regularity” measure \mathfrak{R} , since the matrices with the lowest condition numbers also had low \mathfrak{R} values as shown in Figure 1.

Discussion and Conclusions: The results shown here strongly suggest that when no prior assumptions can be made regarding the imaged object (the k-space energy distribution), and providing regular sub-sampling is possible, then this gives the best reconstruction possible independently of the PPI reconstruction algorithm. Under these circumstances, there is no advantage in employing RF encoding. However, if for other reasons it is desirable to use irregular gradient sampling, then by employing RF modulation the signal can still be redistributed in k-space, recovering the optimal non-RF modulated regularly sub-sampled encoding matrix.

Acknowledgements: EPSRC and Philips for grant funding. **References:** (1) Pruessmann KP et al., 1999, MRM, 42:952; (2) Kyriakos WE et al, 2000, MRM, 44:301; (3) Kyriakos WE et al., 2006, NMR Biomed, 19:379; (4) Nunes RG et al., 2006, ESMRMB, 302; (5) Katscher U and Börner P, NMR Biomed, 2006, 19:393; (6) Bydder M et al., 2002, MRM, 47:160; (7) Pruessmann KP et al., 2001, MRM, 46:638; (8) The MathWorks Inc., release R2006a.

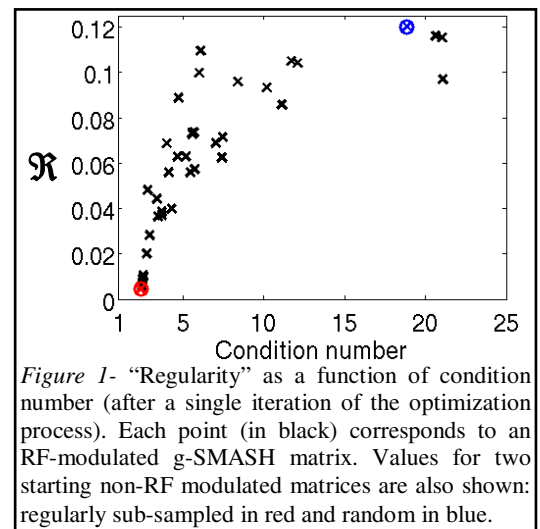


Figure 1- “Regularity” as a function of condition number (after a single iteration of the optimization process). Each point (in black) corresponds to an RF-modulated g-SMASH matrix. Values for two starting non-RF modulated matrices are also shown: regularly sub-sampled in red and random in blue.