Parallel Transmit Pulse Design through "Learning"

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Introduction: Previous studies explored reciprocity between parallel receive (Rx) and parallel transmit (Tx), proposing bridging the two for advancing parallel Tx/Rx MR (1,2). One appealing idea is to improve parallel Tx pulse design by using adapted parallel Rx reconstruction algorithms – with successes bridging the algorithmic aspects of the two fields one can expect the prevalent parallel Rx knowledge/experience to provide a considerable thrust for parallel Tx development. The main goal of the present study was two-fold: to go beyond SENSE algorithm and elucidate an example that connects parallel Tx pulse design with another common parallel Rx reconstruction algorithm, and to address practical challenges in designing robust parallel Tx pulses by leveraging the connection. The present study also aimed at possibly exploiting conditions that are particularly favorable to parallel Tx. Validation results obtained with simulations are presented and discussed.

Methods: It was noted that, for spatial domain parallel Tx pulse design methods, discontinuities at object boundaries of acquired B_1 maps as well as perturbations to the B_1 mapping process tend to cause compromises in aliasing lobe suppression, an effect that is, to some extent, analogous to the significant issue of residual aliasing artifact of SENSE at low spatial resolution (3,4). A promising solution is to apply a spectrum optimization and thereby avoid excitation pulses that create excessive energy at unnecessarily high spatial frequencies. With the sense that excitation pulse design bears an increasingly close relationship with image reconstruction as RF methods continues to evolve, and recognizing GRAPPA and ARC's minimum requirements on B1 mapping as well as low-frequency training principles (5,6), we set out to further explore reciprocity, and to adapt GRAPPA and ARC for improving the robustness of parallel Tx pulse design against B1 mapping issues.

The reciprocity as discussed in a previous study (2) could be illustrated as follows, at least for the case of Cartesian k-space traversing:

reconstructed image $\quad \hat{M}(\mathbf{r}) = \sum_{n=1}^{N} h_r^{(n)}(\mathbf{r}) \left[B_{1-}^{(n)}(\mathbf{r}) M(\mathbf{r}) \right]_{\text{aliased}}$ [1]

created excitation profile $\quad \hat{u}(\mathbf{r}) = \sum_{n=1}^{N} B_{1+}^{(n)}(\mathbf{r}) \left[h_t^{(n)}(\mathbf{r}) u(\mathbf{r}) \right]_{\text{aliased}}$ [2]

$M(\mathbf{r})$ = magnetization profile; $B_{1-}^{(n)}(\mathbf{r})$ = nth Rx coil's sensitivity map;
$u(\mathbf{r})$ = target excitation profile; $B_{1+}^{(n)}(\mathbf{r})$ = nth Tx coil's B_1^+ field map;
number of channels = N in both the parallel Tx and parallel Rx cases;
$[\ ]_{\text{aliased}}$ = aliased finite-bandwidth version resulting from k-space sampling

Note that there are an infinite number of $h_r^{(n)}(\mathbf{r})$ sets that sufficiently satisfy Eqn.1, and there are various ways to derive them, e.g., with SENSE (2). Note also that swapping properly derived h's with the B's does not break either equations. An idea to design pulses based on reciprocity is then:

With Eqn.1: i) Treat B_1^+ maps as B_1^- maps, ii) Treat $u(\mathbf{r})$ as $M(\mathbf{r})$, iii) Compute the aliased images based on the k-space sampling trajectory, and iv) For a chosen parallel Rx recon, derive its corresponding $h_r^{(n)}(\mathbf{r})$'s, the weighting functions that accomplish the reconstruction equivalently.

With Eqn.2: v) Treat the above derived $h_r^{(n)}(\mathbf{r})$'s as the $h_t^{(n)}(\mathbf{r})$'s, and vi) Sample the spatial spectra of the $h_t^{(n)}(\mathbf{r})u(\mathbf{r})$'s according to the k-space sampling trajectory to generate the RF pulse waveforms.

To improve pulse design robustness, for Step iv) the present study chose GRAPPA. Instead of performing a spectrum optimization by solving a large system of equations (4), we used GRAPPA's center k-space training method to derive a set of *smooth* spatial-domain weighing functions, the $h_r^{(n)}(\mathbf{r})$'s. The conversion of GRAPPA k-space kernels to the weighting functions is based on the convolution theorem, as is the case with ARC.

RF pulse design has the luxury that the target excitation profile $u(\mathbf{r})$ is known *a priori*, unlike $M(\mathbf{r})$ in Rx. This provides a Bloch equation-based RF pulse design with great opportunities for optimization. For the GRAPPA training in particular, the present method employs a random noise pattern as $u(\mathbf{r})$ instead of the actual target excitation profile. This facilitates a most comprehensive/robust learning, making the resulting $h_r^{(n)}(\mathbf{r})$'s universally applicable to an arbitrary target excitation profile (i.e., one training is sufficient for all target excitation profiles of practical interest).

Results: While waiting for a properly equipped parallel Tx scanner (4) to be restored, we evaluated the present pulse design algorithm in simulations. The simulations emulated the experiment setup used in testing the spectrum optimization algorithm (4), where an 8-channel parallel Tx array was used to excite a uniform disc phantom oriented in the axial plane and a body coil was used for receive. In one simulation, we had the same task (4) of designing a 5.7-msec parallel excitation pulse (4x acceleration; EPI trajectory with peak gradient strength < 1.6 gauss/cm) to create a target excitation pattern that was a low-resolution rendering the *Mona Lisa* by Da Vinci. Instead of assembling and solving a large system of equations, the present pulse design method 'learned' the $h_t^{(n)}(\mathbf{r})$'s (examples shown as color images in Fig.1) in seconds with the GRAPPA-type algorithm described above. Use of a random noise pattern as $u(\mathbf{r})$ led to $h_t^{(n)}(\mathbf{r})$'s that applied well in creating the target excitation profile. This and additional simulations verified a parallel Tx pulse design algorithm that was, based on reciprocity principle, developed by adapting a common parallel Rx image reconstruction algorithm. The algorithm emphasizes low spatial frequency training/learning, which helps improve the robustness of the designed pulses.
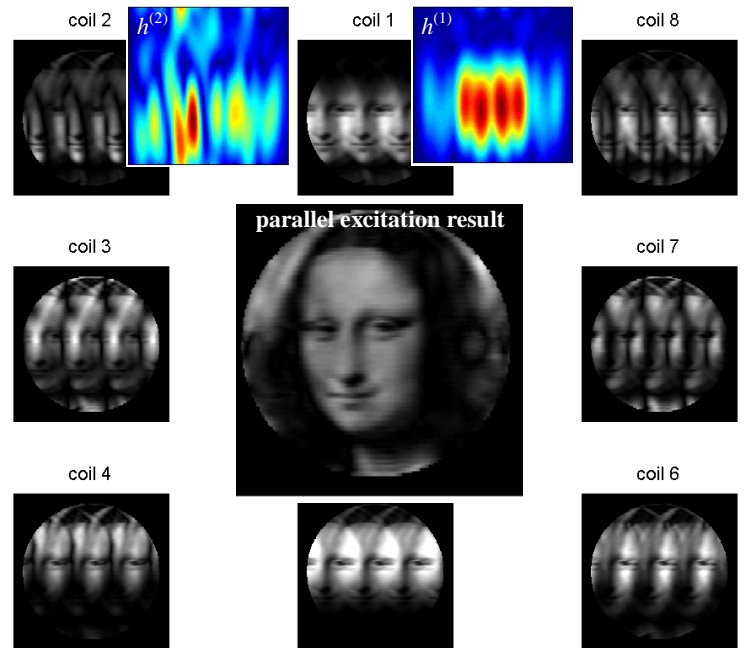

Fig. 2 Simulation results: exciting a uniform disc phantom with a 5.7-ms 2D parallel excitation (center) and with individual channel excitations (perimeter).

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