Estimating K transmit B1+ maps from K+1 scans for parallel transmit MRI

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Introduction: RF transmit coils produce non-uniform field strengths, yielding tip angles that vary substantially over the field of view. In ultra-high MR fields, these variations are particularly severe, causing nonuniform signal and contrast in the image. A map of the B_1^+ field strength (and phase), called a B_1 map, is required to correct this inhomogeneity, through tailored RF pulses [1,2] or proper pre-scan calibration [3]. An accurate map is especially important for parallel excitation (using a coil array). The standard approach to B_1 mapping, the double angle method (DAM) [4], performs best with high flip angles that are hard to achieve across the full object with single coil excitation at high field strengths. DAM also lacks phase estimates and requires at least *2K* scans for *K* transmit coils. Recent proposed methods use coil combinations to achieve larger, more optimal flip angles over the field of view [5,6]. These matrix approaches were combined with existing B_1 mapping methods that often require multiple tip angles per measurement or separate measurements (or previous estimates) for the phase. In this work, we combine matrix approaches with our regularized B_1 estimate that incorporates the effects of slice-selection [7]. We estimate both the magnitude and phase of the complex B_1 map using as few as *K+1* measurements for *K* transmit coils.

Eq. 1

$$y_{jm} = f_j F_2 \left(\sum_{k=1}^{K} \alpha_{mk} z_{jk} \right) + \varepsilon_{jm},$$

Eq. 2

$$(\hat{z}, \hat{f}) = \arg\min_{z, f} \Psi(z, f),$$

$$\Psi(z, f) = L(z, f) + \beta R(z),$$

where

$$L(z, f) = \sum_{j=1}^{N} \sum_{m=1}^{M} \frac{1}{2} \left| y_{jm} - f_j F_2 (\sum_{k=1}^{K} \alpha_{mk} z_{jk}) \right|^2$$

and

$$R(z) = \sum_{k=1}^{K} \beta \, \mathsf{R}(z_k),$$

Eq. 3

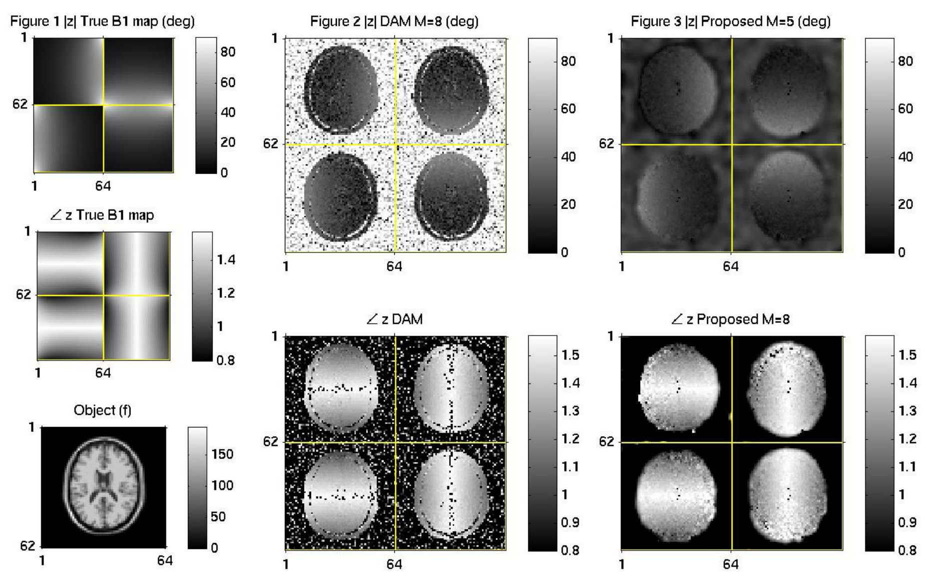
$$f_j = \frac{\sum_{m=1}^{M} \mathrm{real}\left(y_{jm}^* F_2(x_{jm}^{(n)}) \right)}{\sum_{m=1}^{M} \left| F_2(x_{jm}^{(n)}) \right|^2}.$$

Eq. 4

$$x^{(n+1)} = x^{(n)} - D(x^{(n)}, f^{(n)}) \nabla_x \Psi\left(x^{(n)}, f^{(n)} \right),$$

Method: Let *K* represent the number of coils; we take *M* measurements by transmitting with coil combinations and receiving from a common coil. The (possibly complex) matrix $\boldsymbol{\alpha}$ (*M x K*) represents which coils are used for each scan and their relative amplitudes. Possible coil combinations include: one-at-a-time (standard method), leave-one-out [5], or constant-amplitude/varying-phase [6]. The same RF pulse drives each coil simultaneously with relative amplitudes denoted α_{mk} and the fields add linearly. We model the resulting signal measurements in (Eq. 1) where *j* denotes the pixel value, ε_{jm} is (complex) noise, f_j is the underlying object transverse magnetization and z_{jk} denotes the (complex) B_1 map. The function F_2 replaces the typical *sin* function in DAM and inherently incorporates slice selection effects that would otherwise cause residual error in both the flip angle itself and its distribution [8]. F_2 is a sinusoidal-like function tabulated using a Bloch equation simulator, thus incorporating MR effects beyond the simplified *sin* model.
To solve for the unknown B_1 maps $\boldsymbol{z_k}$, we jointly estimate $\boldsymbol{f}$ and $\boldsymbol{z_k}$ by solving the penalized least-squares minimization problem in Eq. 2. Because B_1 maps are inherently smooth, we regularize the maps. $R(\boldsymbol{z_k})$ is a regularizing roughness penalty where β is a parameter that controls the smoothness and, here, is chosen empirically. When $\boldsymbol{\alpha}$ is well-conditioned and invertible, we choose to estimate the M composite maps and finally solve for the B_1 maps by inverting the matrix $\boldsymbol{\alpha}$. When $\boldsymbol{\alpha}$ is ill-conditioned, we can estimate the B_1 maps directly in a similar amount of computation time. We use iterative methods and a block minimization method where we first estimate $\boldsymbol{x}$ and then $\boldsymbol{f}$ during each iteration, using the current value of the maps. The minimizer with respect to $\boldsymbol{f}$ is found analytically (Eq. 3). We use quadratic majorizer principles to derive an iterative estimate of $\boldsymbol{x}$ that has the form (Eq. 4) where *D* is a diagonal matrix.
To reduce scan time, we desire $M \approx K$. We propose using *M=K+1* measurements, using leave-one-out coil combinations for the first *K* measurements and then double one row of the $\boldsymbol{\alpha}$ matrix (i.e., use twice the tip angle for the one of the coil combinations) for the last measurement. As long as there are not too many signal voids, we can use these two matching measurements and the DAM [3] and (Eq. 3) above to initialize our algorithm for $\boldsymbol{x}$ and $\boldsymbol{f}$. If the signal void from the missing coil is too large, we can use *M=K+2* total measurements.

Results and Discussion: We investigated for our method using a simulated brain image [9] and simulated complex B_1 maps based on equations for a magnetic field in a circular loop [10] (true object and B_1 maps shown in Figure 1). We simulated *K=4* coils and used *M=5*, using leave-one-out for the first four coil combinations and doubled the relative amplitudes of the first measurement for the last measurement. We assumed a truncated sinc pulse and used it to tabulate F_2 for the algorithm. We added complex Gaussian noise for a final SNR of approximately 27 dB. We used our iterative algorithm and compared to the standard DAM method (using *M=8* single coil excitations) as well as using our matrix approach with *M=8* (doubling the tip angle of each of the first 4 measurements), both with single-coil excitation and leave-one-out excitation. We used an empirically controlled parameter ($\beta=2^{-8}$) for all simulations and 250 iterations. The standard DAM method (*M=8*) in Figure 2 is very noisy and has a high NRMSE (37% $|\boldsymbol{z}|$ and 37% phase $\boldsymbol{z}$), especially in pixels with low signal (skull and nasal area NRMSE of 114% $|\boldsymbol{z}|$ and 68% phase $\boldsymbol{z}$). The proposed method in Figure 3 with *M=5* and using leave-one-out as described has a lower NRMSE both over the whole object (9% $|\boldsymbol{z}|$ and 11% phase $\boldsymbol{z}$) and in pixels with low signal (13% $|\boldsymbol{z}|$ and 24% phase $\boldsymbol{z}$). The proposed method with *M=5* has similar levels of NRMSE to the *M=8* methods when we use enough iterations. The proposed method has smoother maps which interpolate into signal voids. Overall, this method uses a smaller number of measurements, incorporates slice selection effects, and is more accurate than conventional methods.



[1] Saekho, et al. MRM 2005; 53(2):479-483. [2] Sung, et al. MRM 2008; 59(3):441-446. [3] Cunningham, et al. MRM 2006; 55(6):1326-1333. [4] Akoka, et al. Mag. Res. Im. 1993; 11(3):437-441. [5] K. Nehrke, et al. Proc. ISMRM 16 (2008) p. 353. [6] D. Brunner, et al. Proc. ISMRM 16 (2008) p. 354. [7] A. Funai, et al. Proc. ISMRM 16(2008) p. 3145 [8] J. Wang, et. al. MRM 2006; 56(2):463-468. [9] Collins, et al. IEEE-TMI 1998; 17(3):463-468. [10] Y. Wang, et al. MRM 2000; 44(3):495-499. Supported in part by a NSF-GRF and NIH Grant R01NS058576.