Adaptive Self-Calibrating in k-Space Parallel Magnetic Resonance Imaging using Kalman Filter

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Introduction: In k-space based parallel MRI (pMRI), variable density sampling is typically employed and spatial correlation (convolution kernel) among neighboring signals is calculated in calibration to reconstruct missing signals [1]. However, it is often challenging to obtain accurate calibration information due to data corruption with noises and spatially varying correlation. To tackle these problems, we develop a novel, adaptive self-calibration method in k-space pMRI under a framework of the Kalman filter (KF), modeling the static calibration region in k-space into a dynamic discrete linear system.

Theory: The Kalman filter is commonly used to estimate the states of a dynamic system using the step-wise multiple regression method. To employ dynamic feature, measurement models, S_n^{ACC}, and target calibration models, $S_{\gamma,n}^{CAL}$, are transformed into dynamic calibration information updating with increasing steps using two groups of measured source signals sliding bi-directionally from the central to the peripheral k-space within the Nyquist-sampled calibration from static calibration information, as shown in Fig.1, thus considering spatial variation of convolution kernels and making it possible to reduce computation burden by dealing with small matrix size, where n and γ are the step and coil index respectively. Fig. 2 illustrates a schematic of the proposed KF self-calibration in k-space pMRI. it is assumed that initial estimates of convolution kernels, $\hat{X}_{\gamma,0}$, and error covariance of the convolution kernels, P_0^+, are set to zeros and the process noise, W, has a zero mean normal distribution, and is statistically independent with pre-scanned measurement noise, V. In the predict phase, self-calibration is formulated using dynamic discrete linear state space model. Since convolution kernels remain identical with increasing steps due to linearity of Fourier transform but in practice vary within some uncertainty, identity state transition model($A_n=I_n$) with the pre-defined process noise is employed, and spatial variation of correlation among neighboring k-space points is considered by updating S_n^{ACC}. Using these models, *a priori* convolution kernels at the current step, $\hat{X}_{\gamma,n}^-$, are estimated by combining $\hat{X}_{\gamma,n-1}$ and W, and estimated target calibration signals, $\hat{S}_{\gamma,n}^{CAL}$, are then calculated using S_n^{ACC} and V. P_n^- is calculated by adding P_{n-1}^+ to the process noise covariance, Q. In the update phase, optimal update gain, K_n, is computed at each step using P_n^-, S_n^{ACC}, and D, where K_n is the weighted averaging factor between measured and ideal convolution kernels, and D is a diagonal matrix composed of the noise variance for each coil. $\hat{X}_{\gamma,n}^-$ is then combined with the Kalman gain adjusted residuals between $S_{\gamma,n}^{CAL}$ and $\hat{S}_{\gamma,n}^{CAL}$, refining the *a posteriori* convolution kernels, $\hat{X}_{\gamma,n}^+$, which obtains an intermediate value between the measured and ideal noise-free convolution kernels. Before moving to the next step, a sliding group-wise update of S_{n+1}^{ACC} and $S_{\gamma,n+1}^{CAL}$ is performed, and is checked whether or not both matrices are within the Nyquist-sampled calibration region. Iteration continues as long as those matrices are within the calibration region.

Method and Results: To test the proposed technique, a brain data is acquired in a healthy volunteer at 3T whole-body scanner (MAGNETOM Trio, Siemens Medical Solutions, Erlangen, Germany) using 2D spoiled gradient echo imaging with following parameter: FA, 70°;TE, 2ms; TR, 22ms FOV, 256mm x256mm; in-plane acquisition matrix, 256x256; slice thickness, 4mm. A twelve-channel head coil is used for signal reception. To emulate under-sampling for the proposed method, the fully acquired data are decimated using a factor of 4 with 32 self-calibrating lines in the central k-space. Four images are reconstructed using conventional, shifted (calibration region from the middle to the periphery of the Nyquist sampled central k-space), high pass (image support reduction), and the proposed KF self-calibration for comparison. The conventional calibration methods yield artifacts and amplified noises particularly in the central region of the image while the proposed KF self-calibration retains a low level of artifacts and noises in the corresponding region.

Conclusion and Discussion: We presented the formulation and solution for a novel adaptive self-calibrating pMRI method using a framework of the Kalman filter. The proposed KF self-calibrating pMRI in k-space is potentially a promising and efficient solution even at high reduction factors. It would be advantageous to investigate the step-variant process noise model and the weighted state transition model in the future.

Reference: [1] Griswold et al., MRM 47:1202-10 (2002) [2] J. Park et al., MRM 53:186-193 (2004) [3] Z. Wang et al., MRM 54:738-742 (2005) [4] D. Simon, Optimal state estimation: Kalman, H∞, and nonlinear approach: John Wiley, 2006

Figure 2. An overall schematic of the proposed, KF sliding group-wise self-calibration in the Nyquist sampled calibration region.
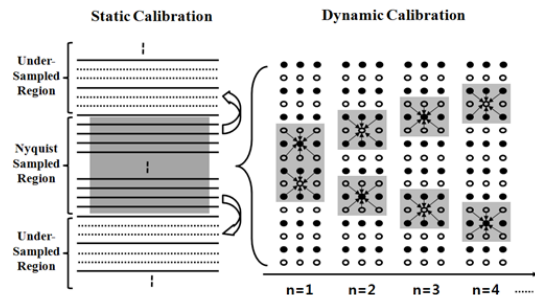

Figure 1. The proposed dynamic calibration model sliding group-wise bi-directionally from the low to high spatial frequency with increasing steps, and corresponding model
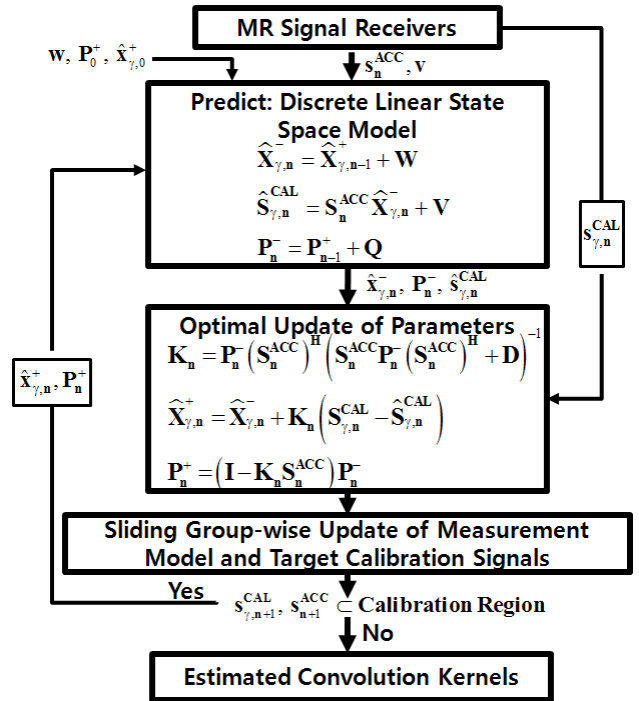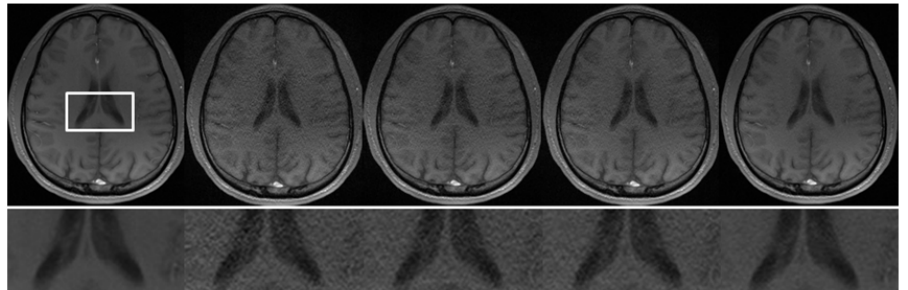

Figure 3. Comparison of images reconstructed using four different calibration. Top row: reference image, conventional, shifted, high pass, the proposed calibration (from left to right). Bottom row: the corresponding zoomed image in the white box. Note that the proposed calibration highly reduces residual artifacts and noises.