Multi-Scale Subband Weighted Partially Parallel Imaging

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Introduction: Combination of partially parallel imaging (PPI) and compressed sensing (CS) [1-4] employs complementary properties of the two competitive methods. Among them, direct combination approaches [1-2], which jointly consider both CS and PPI constraints, potentially suffer from image artifacts at high acceleration, because sparsifying transform are less coherent with sensitivity encoding than Fourier encoding. Then, combination of CS and PPI in a sequential fashion [3-4] was recently introduced, demonstrating its feasibility in overcoming the aforementioned problems. In this work, we develop a novel, multi-scale subband weighted PPI algorithm, wherein 1) CS is utilized to yield multi-scale sparse solutions, 2) Subbands in each scale are employed to produce multiple de-noised filtered k-spaces, 3) Join estimation of PPI convolution kernels and k-spaces are performed, considering both inter-subband correlation and spatial correlation over multiple coils.

Method: A flowchart of the proposed, multi-scale subband weighted PPI algorithm is shown in Fig. 1. Variable density (VD) pseudo-random under-sampling pattern, in which data is fully acquired in the central k-space while randomly under-sampling in the peripheral k-space, is employed to produce sufficient incoherence between the sparsifying and Fourier operators. **1) CS optimized sparse solution in multi-scale domain**: Missing signals in individual coil k-space are estimated by solving the CS optimization problem: $\|w\|_{\ell_1},\ s.t.\ \|y - D_s F\Psi^* w\|_2^2$ (1), where w denotes wavelet coefficients, F is the Fourier transform, Ψ is the sparsifying transform, D_s is the sampling operator, and y is the measured data. **2) Generation of subband driven multiple de-noised filtered k-spaces:** CS optimized sparse solution results in a globally de-noised k-space: $X = F\Psi^* w$ (2), X is the full reconstructed k-space. An individual subband at each scale in the wavelet domain is multiplied by a binary mask (a subband of interest: 1, other subbands: 0), producing multiple subband weighted k-spaces with the spectral profiles as shown in Fig. 1: ${}^{w}X_{d,j} = F\Psi^* M_{d,j} w$ (3) where ${}^{w}X_{d,j}$ is the subband weighted k-space depending on both directionality and scale (d=HL,LH,HH, j=1,…J), and $M_{d,j}$ is the binary subband mask in the wavelet domain. **3) Joint estimation of subband weighted PPI convolution kernel and k-space:** Considering both the globally de-noised k-space and the subband weighted multiple k-spaces, we calculate PPI convolution kernel during coil calibration as: $x_c(k) = \sum_{c'} x_{c'} \otimes g_{c'} + \sum_{c'} {}^{w}x_{c'} \otimes h_{c'}$ (4) where c and c' are the coil indices, $g_{c'}$ and $h_{c'}$ is the convolution kernels for the global and the subband driven k-spaces, respectively, and $\otimes$ is the convolution operator. As compared to conventional PPI, a major contribution of the proposed method is to incorporate both inter-subband correlation and spatial correlation over multiple coils in coil calibration. Additionally, it can be interpreted that the first term in Eq. (4) is equivalent to conventional convolution in PPI while the second one in Eq. (4) to the generalized high-pass filtered convolution in PPI [5-6]. Exploiting the proposed convolution approach, we jointly estimate both convolution kernel and k-spaces by solving the following optimization problem: $\{X, G\} = arg \min_{X,G} \frac{1}{2}\|GX - X\|_2^2 + \frac{\lambda_1}{2}\|y - D_s X\|_2^2 + \frac{\lambda_2}{2}\|D_{ns} G X\|_2^2$ (5), where G denotes the convolution kernel, D_{ns} is the non-sampling operator, λ_1 and λ_2 is the parameter to control data fidelity and non-measured data instead of penalizing fully reconstructed k-space, respectively. Solution in Eq.5 is found with respect to two variable, X and G, separately while keeping the other one fixed using a standard gradient descent method such as conjugate gradient (CG) algorithm. Once the optimal solutions, X and G in (5) is calculated, subband driven partial k-space is regenerated and the iteration process is repeated until the error of the reconstructed k-space at the two successive iteration steps become negligible.

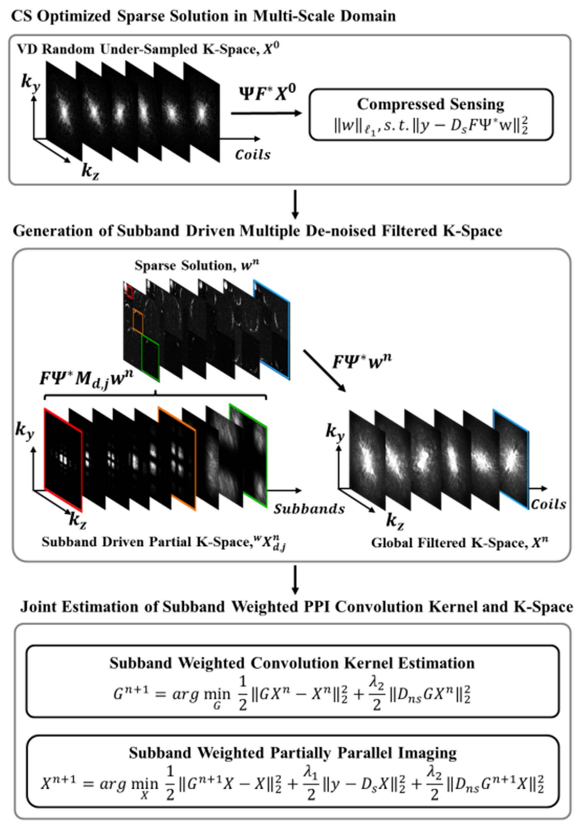

Figure 1: *A Flowchart of the proposed multi-scale subband weighted partially parallel imaging.*

Results: A brain in vivo data (256x256) is simulated for an 6-channel head coil. To emulate under-sampling for the proposed method, the fully acquired data are decimated using a factor of 9. For comparison, two images are reconstructed using ℓ_1 SPIRIT and the proposed multi-scale weighted PPI technique. ℓ_1 SPIRIT restore image details but yields ringing artifacts at the boundary of brain (solid arrow in Fig. 2a-b). Additionally, low contrast structure is destroyed noises propagates over the entire image (Fig. 2c). Compared to ℓ_1 SPIRIT, the proposed technique successfully eliminates ringing artifact in the solid-arrow-pointed region (Fig. 2d-e) and suppresses noises to a certain degree, reducing pronounced errors (Fig. 2f).

Conclusion and Discussion: We proposed an efficient joint estimation algorithm of kernel and k-space iteratively considering inter-subband correlation as well as multiple coil correlation, effectively decoupling CS and PPI with no direct tradeoff of image accuracy with noise even at high acceleration factors. Comparison with image reconstructed by ℓ_1SPIRIT confirms that the proposed method is competitive against the existing techniques.

References: [1] Liu et al., ISMRM 2008, p.3154, [2] Lustig et al., MRM 64:457-471 (2010), [3] Liang et al., MRM 62:1574-1584 (2009), [4] Huang et al., MRM 64:1078-1088 (2007), [5] Huang et al., MRM 59:642-649, [6] Park et al., ISRMR 2012, p.2230.

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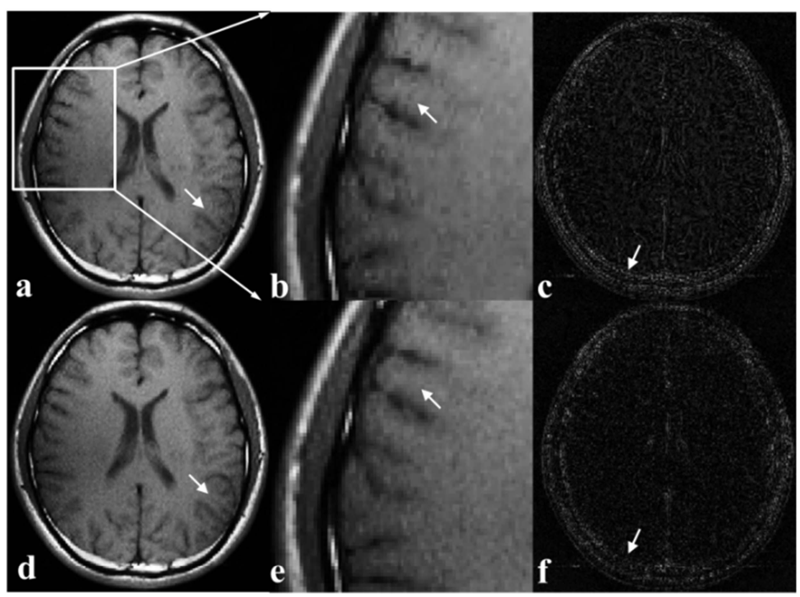

Figure 2: *Comparison of images reconstructed using: ℓ_1 SPIRIT (a-c), and the proposed method (d-f) at a high acceleration factor of 9. Each column consists of reconstructed images, zoomed images, and error images.*