PROMISE: Parallel Reconstruction with Optimized acquisition for Multi-contrast Imaging in the context of compressed Sensing

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Target Audience: MR researchers on reconstruction and clinical scientists working on multi-contrast studies.

Purpose: A typical clinical MR examination is composed of a number of scans to acquire images with different contrasts. If the same field of view (FOV) is scanned, there is significant amount of sharable information among these images. It has been proposed to use manifold sharable information among multi-contrast images for fast imaging[1-3]. In this work, a specific implementation, Parallel Reconstruction with Optimized acquisition for Multi-contrast Imaging in the context of compressed SEnsing (PROMISE), is proposed to make this high potential method more accurate and clinically applicable.

Methods: With the assumption that the same FOV is scanned, coil sensitivity maps, image structural information and optimal acquisition trajectory were extracted from previously acquired/reconstructed data to enhance the reconstruction of another scan. Fig. 1 demonstrates the flowchart of the proposed scheme in which both the acquisition and reconstruction are optimized. **Sensitivity information** was implicitly extracted through the calibration of GRAPPA operator and SPIRiT convolution kernels, using the recovered k-space from previous scans. In order to estimate the spatially adaptive regularization weights, **sharable structural information** was extracted from previous images as multi-level bands whose values are proportional to the probability of existing boundaries[4]. **Sampling trajectories** were optimized using a modified iterative optimization scheme. The optimization scheme is highly efficient by using pre-computation and pseudo-reconstruction.

Taking the reconstruction of a T2w image using sharable information from the T1w scan as an example, there are 4 major processes for PROMISE: 1) Reconstructing a T1w image at low reduction factor using SENSE; 2) Extracting manifold sharable information from the reconstructed T1w data as described before; 3) Partial recovery of T2w k-space using GRAPPA operator; 4) Reconstructing T2w image with extracted information by solving:

$$\min_{x} E(x) = \left\| \hat{D}x - k \right\|_2^2 + \lambda_0 \left\| \hat{G}x - x \right\|_2^2 + \lambda_1 \left\| W_n \Psi\left(F^{-1}x\right) \right\|_1 + \lambda_2 \left\| W_I \nabla\left(F^{-1}x\right) \right\|_1$$
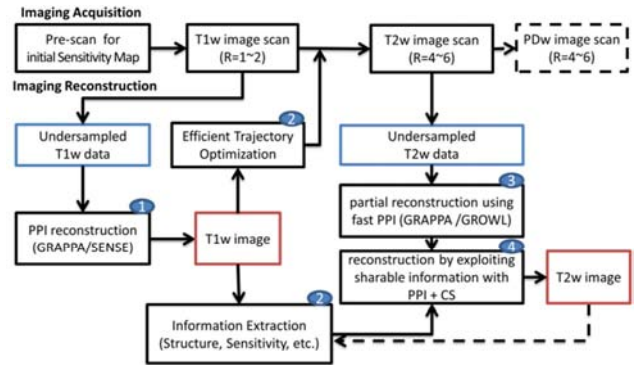

Fig. 1 Flowchart of PROMISE. Both acquisition and reconstruction are optimized for multi-contrast scans. The sampling trajectory is optimized for new acquisition. The sharable information of structure and sensitivity is exploited to enhance reconstruction.

Here X is the k-space to be recovered in T2w scan. Based on the extracted structural information from T1w scan, W_n and W_I are adaptive weights in wavelet and image domain respectively. $\hat{D}$ is the optimized sampling pattern and $\hat{G}$ is the extracted SPIRiT kernel. Similar to the notations in L1-SPIRiT[5], Ψ is wavelet transform, $\mathcal{F}$ is Fourier transform and ∇ is TV operator.

Results: Two in-vivo brain scans (T1w and T2w) were acquired on a Philips 3T system (Philips Healthcare, Best, the Netherland) with an 8-channel head coil (Invivo Corporation, Gainesville, FL). FFE sequence was used for both datasets. The PE direction was left-right. L1-SPIRiT[5] and Correlation[2] Imaging were implemented for comparison. All datasets were fully acquired and retrospectively undersampled in experiments. The computational complexity of PROMISE is the same as L1SPIRiT and it takes about 30 seconds for the additional step to optimize a 1D undersampling trajectory for PROMISE. Figure 2 compares 3 algorithms (L1SPIRiT, Correlation Imaging, and PROMISE) for the reconstruction of in-vivo T2w image at net reduction factor of 5 along PE direction. Error maps are shown in the bottom row and scaled 5x. To test the impact of inter-scan motions to the proposed method, in-plane motion was simulated with 5° rotation and 2-by-2 pixel translation. Figure 3 demonstrates the reconstruction results (reduction factor of 4) and corresponding error maps using Correlation Imaging and PROMISE for the T2w image which was displaced from the reference T1w image.

Discussion: From a recovered full k-space, more accurate convolution kernels could be estimated. Besides, the spatially adaptive regularization can be used from the extracted structural information and optimal sampling trajectory could also be estimated and used for data acquisition. As Fig. 2 shows, compared with previous method using parallel imaging and compressed sensing, PROMISE takes full advantages of the sharable information between multi-contrast scans to achieve a better performance. Moreover, as shown in Fig. 3, PROMISE is more robust to inter-scan motions than previously proposed multi-contrast joint reconstruction scheme[2,3]. This is because the adaptive weights were used for soft regularization based on statistical estimation in image and wavelet domain. Additionally, the k-space implementation uses a small size convolution kernel, which corresponds to the low resolution smooth sensitivity maps that should not be changed by moderate motions.

Conclusion: PROMISE extracts and exploits the sharable information from previously acquired/reconstructed scans with different contrasts. The results demonstrated that PROMISE can achieve a better balance between lower noise level and fine structural details than the method without using sharable information, and a better tolerance to inter-scan motions than existing methods using sharable information.

References: [1] Huang F, et al. ISMRM 2012; p2539 [2] Li Y et al., MRM 2012; [3] Bilgic B et al., MRM 2011; 66(6):1601-1615 [4] Gong E et al., ISMRM 2012; p2269 [5] Lustig M, et al. MRM 2010; 64(2):457-471
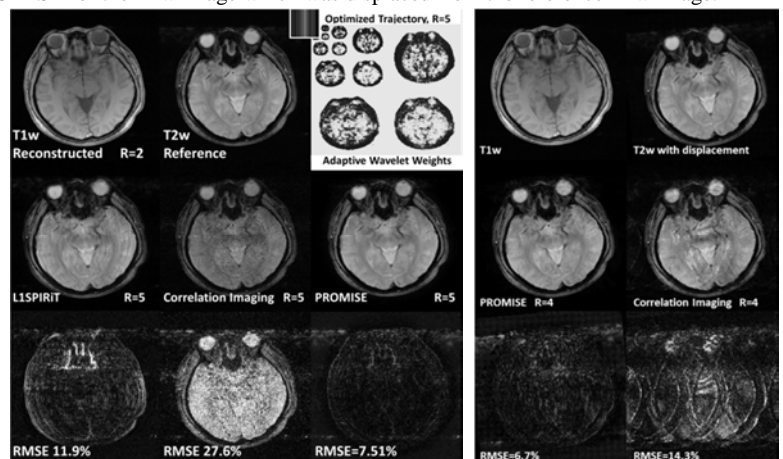
Fig.2 Comparison between PROMISE, L1SPIRiT and Correlation Imaging of a T2w scan at reduction factor of 5. In PROMISE, manifold sharable information is extracted from T1w data for T2w scan. Sampling trajecotry is optimized. Sensitivity kernels and adpative weights are extracted and used to achieve better reconstruction.

Fig.3 Compares PROMISE and Correlation Imaging on a T2w scan with simulated displacement from T1w scan. PROMISE results in smaller error and fewer artifacts caused by interscan motions.