Compressive Sensing Reconstruction for Multi-Contrast Data with Unequal Acceleration Rates

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Synopsis

In multi-contrast acquisitions, a critical concern is whether to distribute undersampling uniformly or unequally across contrasts, as scan times and SNR typically vary among sequences. This study investigates a compressive sensing framework in jointly reconstructing multi-contrast data with unequal acceleration rates. Using *in-vivo* and numerical datasets, the total scan time was fixed and acceleration factors were varied between protocols. The results suggest using lower acceleration rates for protocols with higher-SNR and shorter duration, and higher rates for protocols with lower-SNR and longer duration improves image quality, even in the highly accelerated contrast. The method was also compared to seven state-of-the-art methods from the literature.

Introduction

This study investigates a compressive sensing (CS) framework in jointly reconstructing multi-contrast MRI data with unequal acceleration rates.

Multi-contrast images are commonly acquired to maximize complementary tissue information, albeit at the cost of longer scans. CS can be used to accelerate scans[1], and image quality improvements have recently been demonstrated through joint reconstruction of multi-contrast images[2-4]. Because scan times and SNR typically vary among sequences in a multi-contrast protocol, a critical concern is whether to distribute undersampling uniformly or unequally across contrasts, which remains a topic understudied.

Here, we investigate the effects of unequal acceleration among contrasts on reconstruction quality on *in-vivo* and numerical datasets consisting of three-contrasts (T1-, T2-, PD-weighted) by fixing the total scan time and varying acceleration factors between protocols. Then, we compare the efficacy of common reconstruction methods for multi-contrast CS-MRI, along with a joint reconstruction framework that we recently proposed[5,6]. We investigate the reliability of these methods against leakage of uncommon features across contrasts, a major concern for joint reconstruction[7].

Methods

We recently proposed a joint reconstruction framework (SIMIT-CS[5,6]: Simultaneous use of Individual and Mutual Information Terms in Compressive Sensing) for CS that simultaneously uses individual and joint regularization terms across multiple contrasts. While joint terms (Group-L1-Sparsity[2] and Color-TV[8]) improve image quality by better utilizing shared information among contrasts, individual terms (L1-sparsity and TV) increase sensitivity to unique information in each contrast to prevent leakage of features across contrasts. Here we used SIMIT-CS to jointly reconstruct multi-contrast datasets and compared SIMIT-CS with an implementation that only uses individual terms (Hybrid-IRWALM[9]), and six other state-of-the-art reconstructions methods (SparseMRI[1], TVCMRI[10], recPF[11], GSMRI[2], FCSA[12], FCSA-MT[4]).

<u>Simulated Data:</u> Simulations were performed using Matlab (Mathworks Inc.,Natick,MA) with a numerical-dataset generated from a segmented brain phantom[13]. Regularization parameters were optimized for each method (interval-search algorithm seeking maximum structural-similarity-index [SSIM] for 3-fold accelerated 5-contrast numerical-dataset [PD-T1-T2-FLAIR-STIR]), and used for all reconstructions hereafter. First, SIMIT-CS and Hybrid-IRWALM were compared in a 3-contrast/two-protocol (PD/T2 acquired together as early/late echoes with TR=2750ms and T1 with TR=550ms) acquisition by fixing the total scan time TA=6:30minutes and varying acceleration factors among protocols. Then, artificial features were added to a subset of images to test methods against leakage-of-features. Reconstructions are given for R_T1=6, R_PD=R_T2=1.9 (TA=6:30minutes). Reconstruction quality was assessed via SSIM, mmE (mean-magnitude error), and nRMSE (normalized root-mean-squared error).

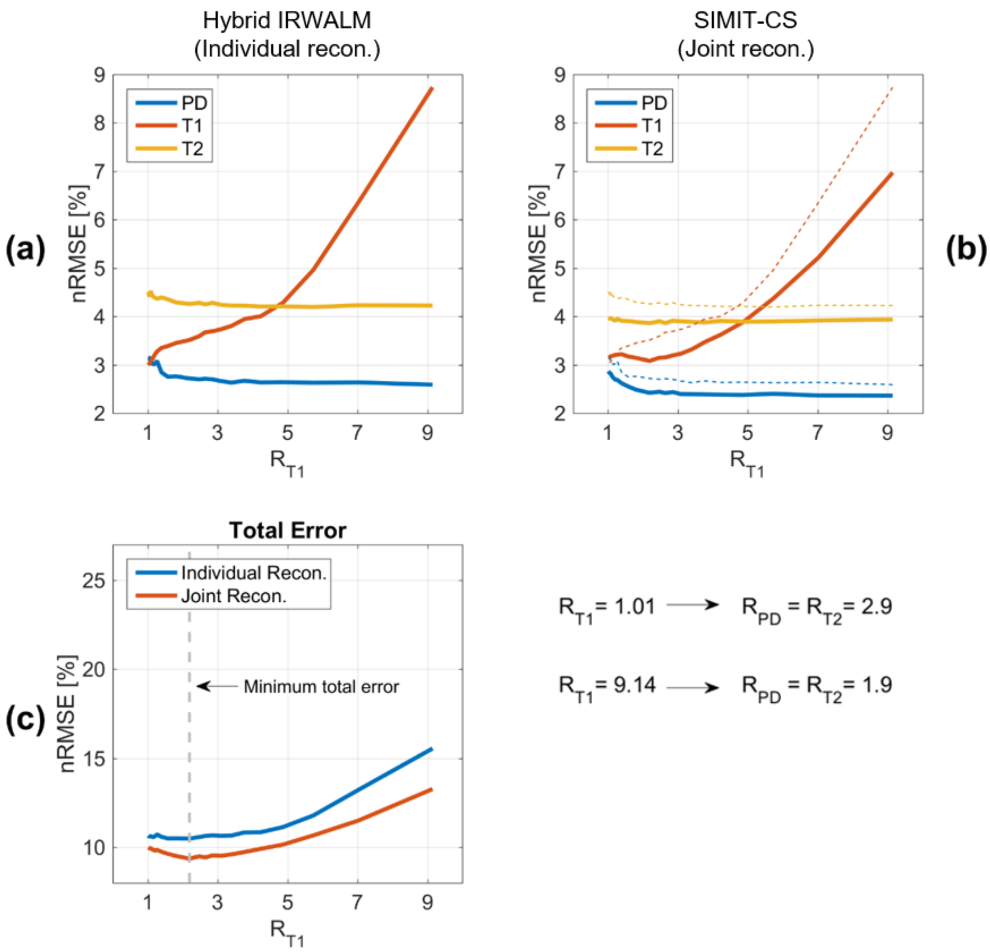

Figure 1: *The total scan time was limited to TA=6:30 minutes (full-data acquisition: 14:05minutes) and the time allocated between the T1- and PD-/T2- (acquired in a single sequence as early/late-echoes) datasets was varied for the numerical-dataset.* ***(a)*** *Image nRMSE for individual reconstruction with Hybrid-IRWALM.* ***(b)*** *Image nRMSE for joint reconstruction with SIMIT-CS (dashed lines show curves for Hybrid-IRWALM.* ***(c)*** *Total image nRMSE across contrasts. All images had comparable SNR, and the minimum total nRMSE was obtained at equal acceleration factors of R=2.2 for all methods.*

In-vivo Data: Experiments were performed on a 3T scanner (Siemens Healthineers,Erlangen,Germany) using a 32-channel receiver (approval of local ethics committee and informed consent of the volunteer acquired). Data were undersampled retrospectively, reconstructed separately for each channel and then combined[14]. Two protocols were used: MP-RAGE (TR=2000ms) for T1-data, and spin-echo (TR=750ms) for PD-/T2-data (acquired together as early/late echoes), with a total scan time of 8:38minutes (PHASExREAD resolution=192x256). SIMIT-CS and Hybrid-IRWALM were compared for various retrospective acceleration rates yielding TA=3:30minutes. *In-vivo* reconstructions are given for R_PD=R_T2=2, R_T1=4 for all methods.

Undersampling Masks: Two-dimensional masks were generated in two phase-encode dimensions. One-eighth of the k-space was fully-sampled. Variable-density random sampling was performed via an nth-order decay with k-space radius, where *n*=max(R-2,3) and R is the acceleration rate. Masks were different across contrasts, but the same among methods.

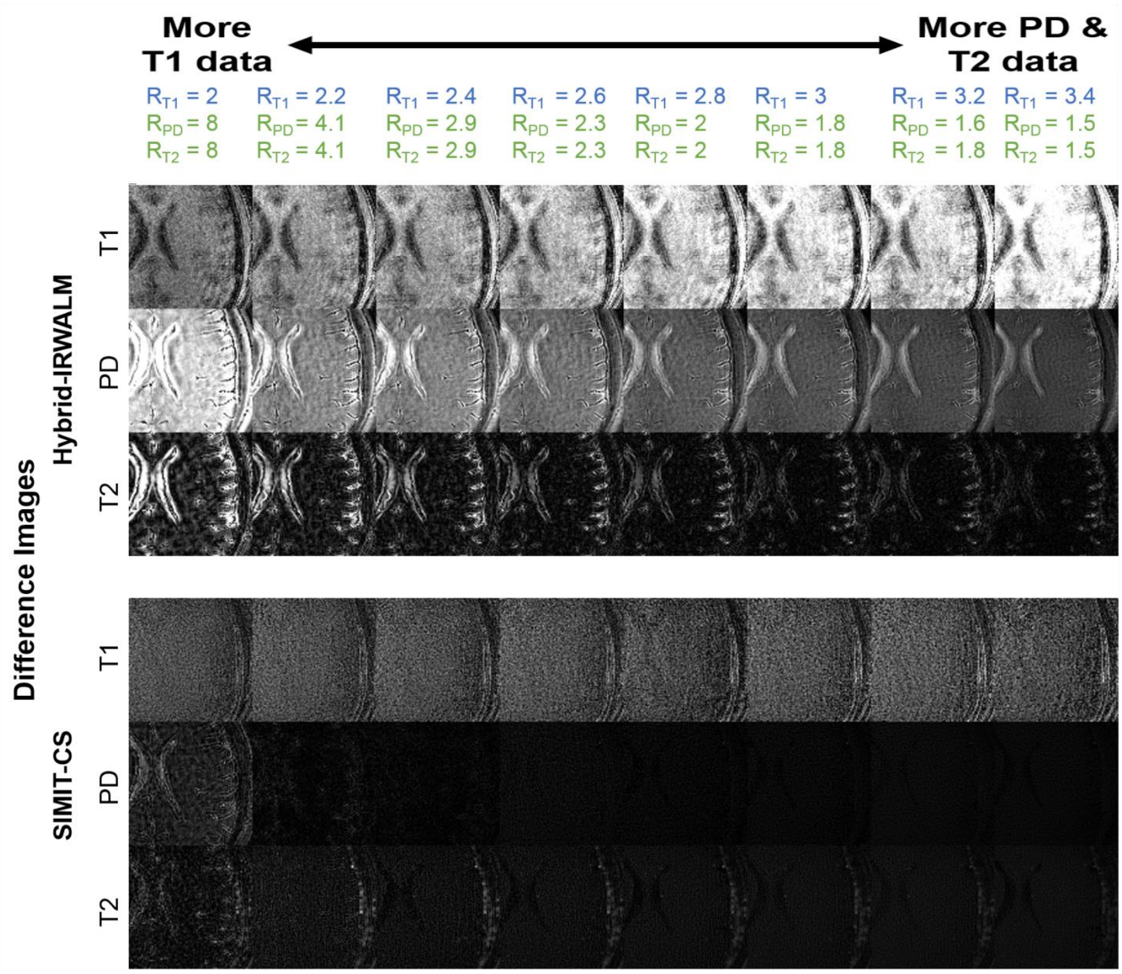

Figure 2: *The total scan time was limited to TA=3:30 minutes (full-data acquisition: 8:38minutes) and the retrospective acceleration rates were varied for the in-vivo dataset. Magnified difference images show the difference between the fully acquired and reconstructed images. The joint reconstruction method SIMIT-CS can exploit the surge of additional data with higher-SNR for higher acceleration rates for T1 (please refer to the text), and therefore, the difference images for T1 are only weakly affected by the amount of acquired T1-data. Lowest total image error across contrasts was obtained for unequal acceleration rates R_T1=2.8 and R_PD=R_T2=2.*

Results and Discussion

Figure 1 shows that for a wide range of acceleration factors with TA=6:30minutes, SIMIT-CS yields lower nRMSE than Hybrid-IRWALM. With all contrasts having comparable SNR, the minimum total error was acquired at a uniform acceleration rate of 2.2 across contrasts.

A similar analysis was made for the in-vivo data (TA=3:30minutes, R_PD=R_T2 varied between 1.8 and 8) with much different results. Remarkably, the difference images for T1 (Fig. 2) were almost unaffected by R_T1 for SIMIT-CS. There are two reasons for this behavior, **i)** due to the difference in TR's, a total of 16 datapoints were acquired for PD- and T2-data for each 3 datapoints skipped for T1-data; **ii)** PD- and T2-data had much higher SNR (5-fold and 3.6-fold, respectively) compared to T1-data in our experiments. SIMIT-CS can utilize this surge of additional information with higher-SNR to make up for skipped T1-datapoints. These results suggest using higher acceleration rates for slower/lower-SNR sequences and lower rates for faster/higher-SNR sequences improve image quality. Here, the total error across all contrasts was minimum for R_T1=2.8 and R_PD=R_T2=2. A similar trend towards unequal acceleration rates was observed in the numerical-dataset when the SNR level of the T1-weighted image was relatively low compared to PD and T2 (not shown).

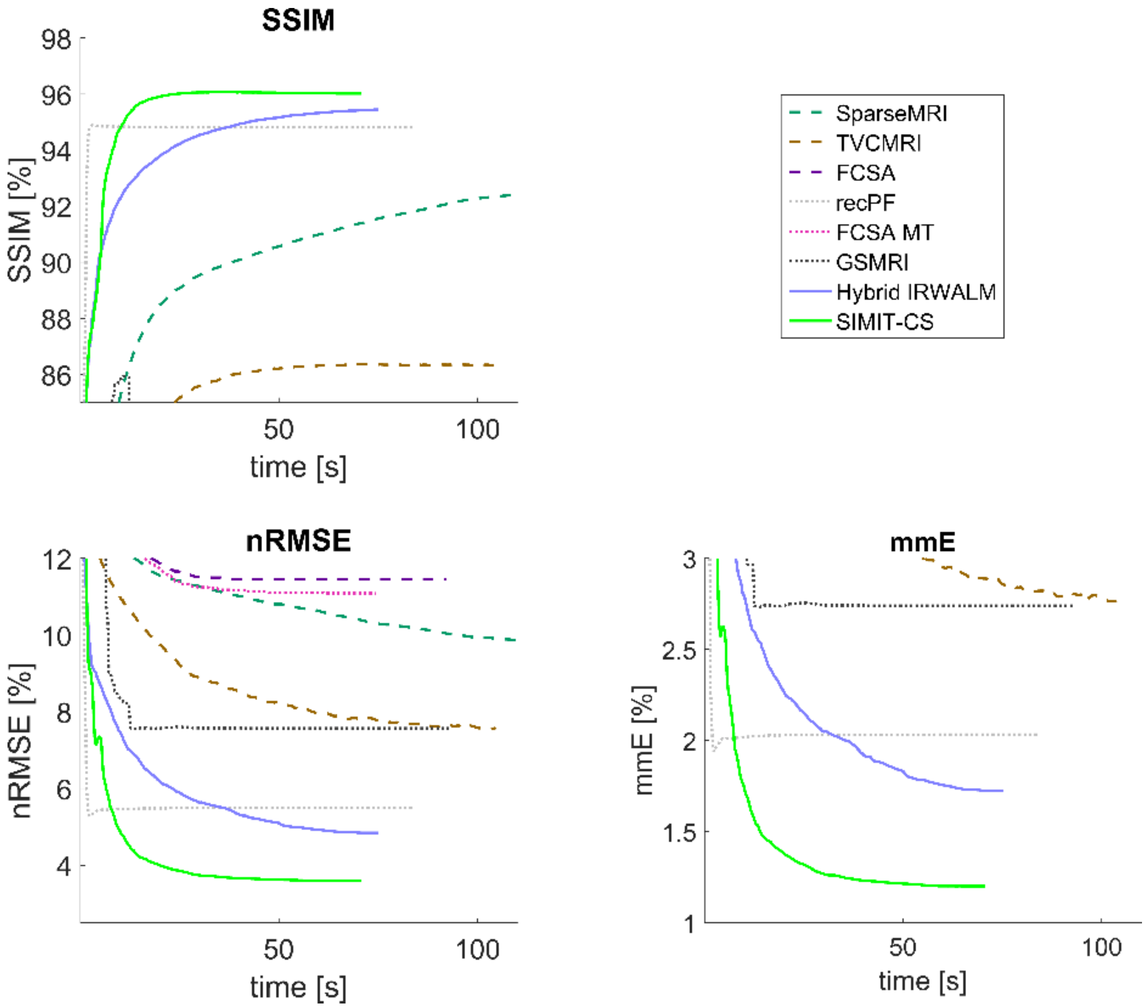

Figure 3: *Simulation results for the numerical phantom for R_PD=R_T2=1.9, R_T1=6 (TA=6:30min). Image metrics were averaged across all contrasts. All methods were run for 200 iterations. Horizontal axes show reconstruction time summed over all threads (i.e., excluding parallel computation capabilities), and were limited to 100s. SIMIT-CS improves image metrics compared to its individual counterparts Hybrid-IRWALM. Complex and noisy images (FoV: 256x256mm, image-size: 256x256) from the numerical brain phantom[13] with artificial non-overlapping features (Fig. 4) were used.*

SIMIT-CS reconstructed higher quality images than reference methods for the numerical-dataset (Fig. 3), and without any leakage-of-features across contrasts (Fig. 4). In-vivo scans also show benefits of joint reconstruction. SIMIT-CS yielded visually sharper images, with another joint method FCSA-MT having the closest performance (Fig. 5).

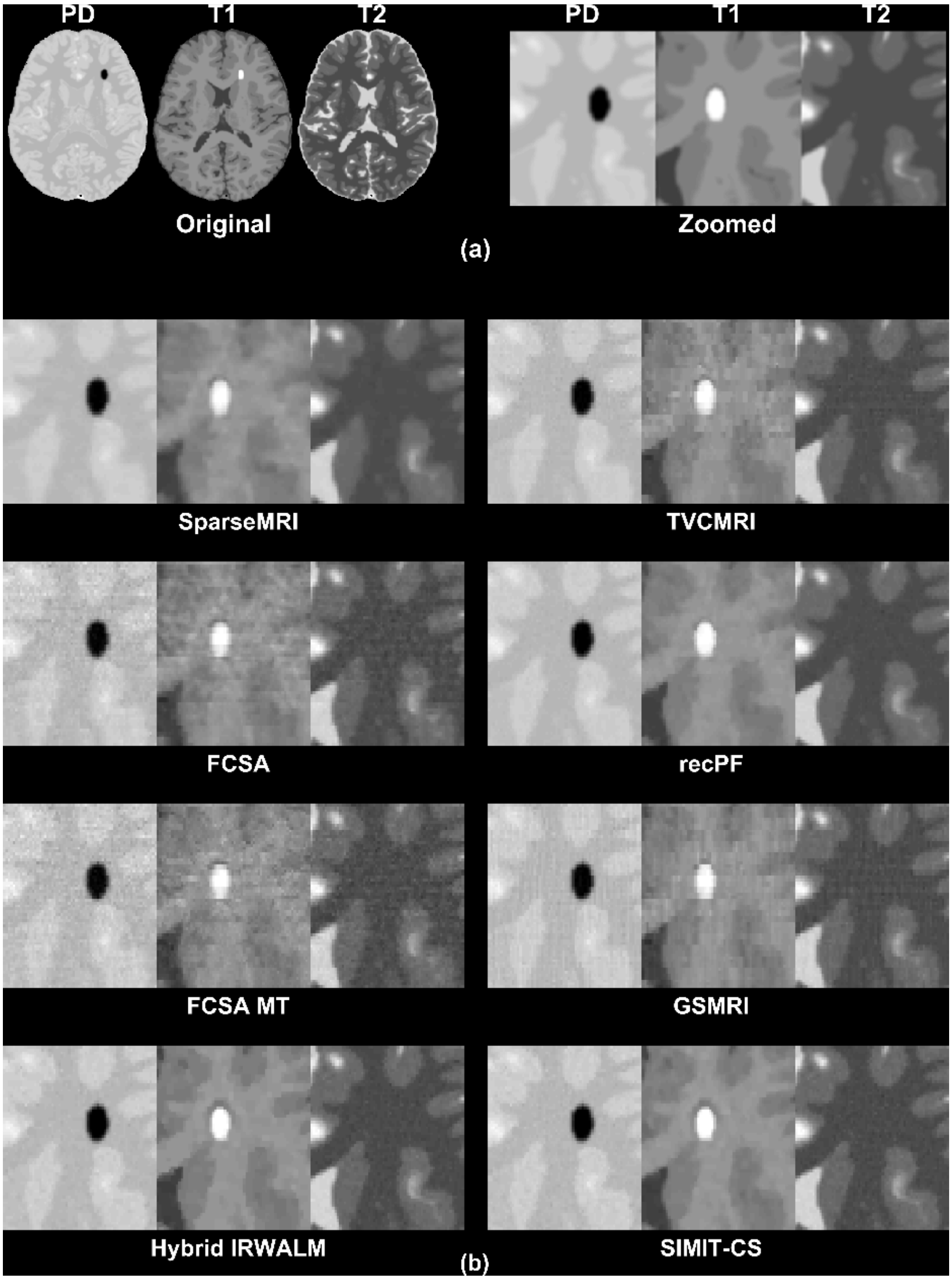

Figure 4: *Magnified reconstructed images are given for all algorithms for R_PD=R_T2=1.9, R_T1=6 (TA=6:30min). All algorithms were tested against leakage of features across contrasts by introducing artificial features (non-overlapping elliptical regions, lower-intensity in PD-image and higher-intensity in T1-image) to the fully-sampled images. While individual reconstruction algorithms Hybrid-IRWALM and RecPF suffer from coarser reconstructions with staircase artifacts in the T1-images, the proposed joint reconstruction framework SIMIT-CS yields visually improved recovery of the features. Complex and noisy images (FoV: 256x256mm, image-size: 256x256) from the numerical brain phantom[13] were used.*

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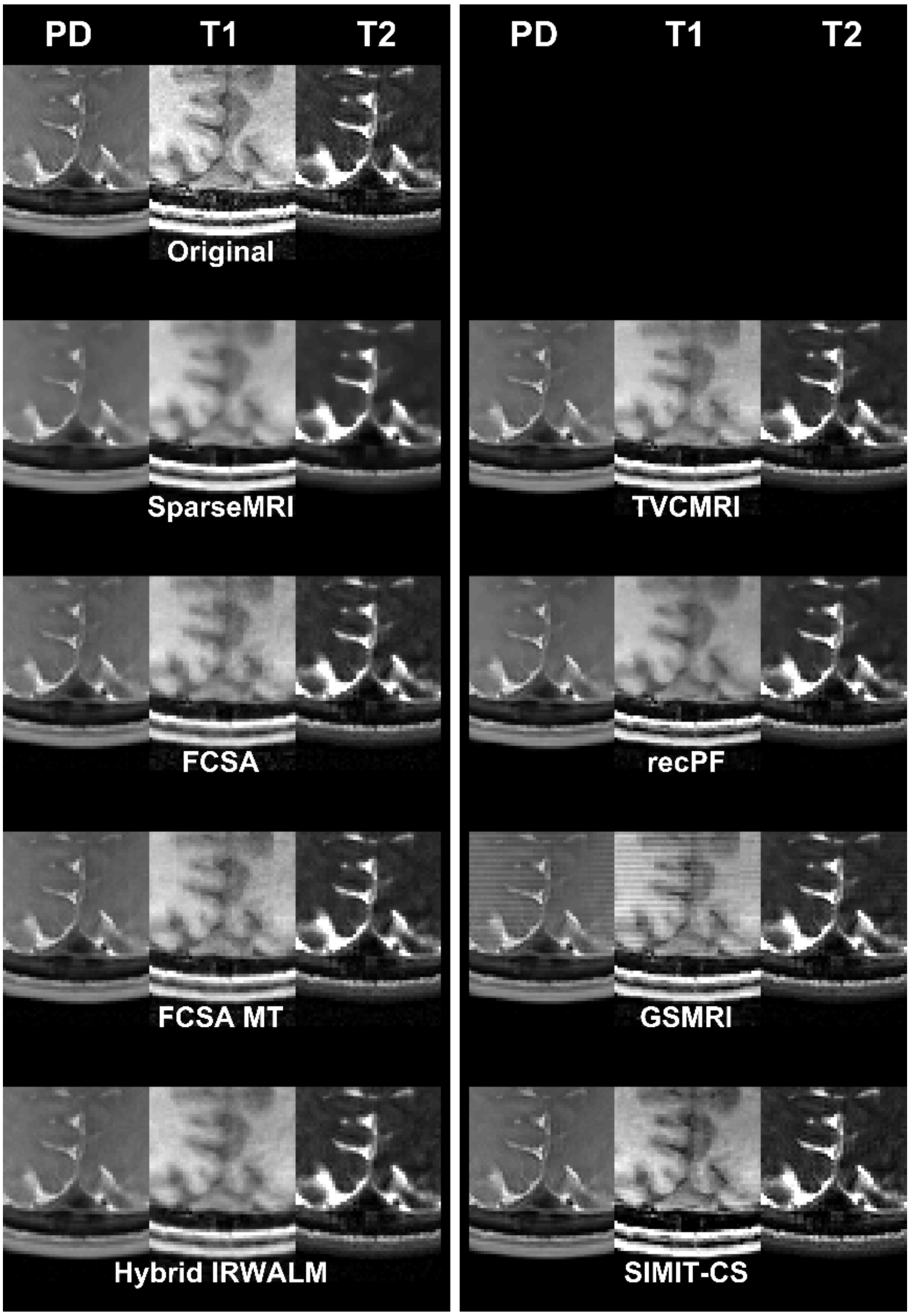

Figure 5: *Methods were compared using experimental data. For each channel of the 32-channel array, the images were retrospectively undersampled (using different masks among contrasts, same set of masks for each method and channel), reconstructed and combined[14] into respective contrast images. For example, for joint algorithms, PD-T1-T2 images of a given channel were jointly reconstructed to yield 32x3 images, to be combined into three images. PD/T2 and T1-images were acquired using TSE and MPGR sequences. Each method was run for 200 iterations. Joint methods SIMIT-CS and FCSA-MT increase sharpness in highly undersampled T1-images compared to their individual counterparts (Hybrid-IRWALM, FCSA, respectively).*

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