Joint Multicontrast MRI Reconstruction

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***Abstract*—Joint reconstruction is relevant for a variety of medical imaging applications, where multiple images are acquired in parallel or within a single scanning procedure. Examples include joint reconstruction of different medical imaging modalities (e.g. CT and PET) and various MRI applications (e.g. different MR imaging contrasts of the same patient). In this paper we present an approach for joint reconstruction of two MR images, based on partial sampling of both. We enforce similarity between the gradient images on top of total variation of each MR image. We examine synthetic phantoms representing T1 and T2 imaging contrasts and realistic T1-weighted and T2-weighted images of the same patient. We show that our joint reconstruction approach outperforms conventional TV-based MRI reconstruction for each image solely. Results are shown both visually and numerically for sampling ratios of 4%-20%, and consist of an improvement of up to 3.6dB.**

I. Introduction

Sparsity-based reconstruction of Magnetic resonance imaging (MRI) exploits prior assumptions on the nature of the data, to overcome imaging artifacts due to insufficient sampling. In many cases, we can utilize similarity to a fully sampled reference image, e.g. an existing scan in a series of MR images [1]. This reference-based MRI [2] approach has been proven to allow significant decrease of the number of measurements required for successful reconstruction [3], in comparison to other compressed sensing [4] based methods. However, when similar MRI images are acquired in parallel or consecutively during the same scan, we can increase the total undersampling ratio by undersampling both images [5]. As images of the same patient have similar spatial characteristics [6], these can be used to perform high quality joint reconstruction of both undersampled images.

In this paper, we focus on joint reconstruction of two different MR imaging contrasts of the same patient. We exploit the similarity between the gradients of the different imaging contrasts, on top of the well known total variation transform for each image. Our approach is implemented via a re-weighting scheme that improves support estimation [7]. It leads to an improvement of up to 3.6dB vs. state-of-the-art MRI reconstruction performed solely on each image.

II. Method

In the joint reconstruction problem our goal is to reconstruct two 2D images of size $N \times N$, $\mathbf{X}_1$ and $\mathbf{X}_2$, from their undesampled measurement vectors, $\mathbf{y}_1$ and $\mathbf{y}_2$. Since in MRI data is sampled in the spatial Fourier domain (a.k.a k-space), we denote by $\mathcal{F}_u : \mathbb{C}^{N\times N} \to \mathbb{C}^{1\times M}$ an undersampled Fourier transform, where $M < N$. In addition, we define: $\mathbf{X} = [\mathbf{X}_1, \mathbf{X}_2]$, $\mathbf{Y} = [\mathbf{y}_1, \mathbf{y}_2]$ and $\mathcal{F}_u\{\mathbf{X}\} = [\mathcal{F}_u\{\mathbf{X}_1\}, \mathcal{F}_u\{\mathbf{X}_1\}]$. Our joint reconstruction unconstrained problem (in a so-called Lagrangian form) can be then formulated as follows:

$$\min_{\mathbf{X}} \underbrace{\|\mathcal{F}_u\{\mathbf{X}\} - \mathbf{Y}\|_2^2}_{term\ 1} + \lambda_1 \underbrace{(TV(\mathbf{X}_1) + TV(\mathbf{X}_2))}_{term\ 2} + \\ + \lambda_2 \underbrace{(\|\mathbf{W}_1 \odot (G_x\{\mathbf{X}_1 - \mathbf{X}_2\})\|_1 + \|\mathbf{W}_2 \odot (G_y\{\mathbf{X}_1 - \mathbf{X}_2\})\|_1)}_{term\ 3}, \tag{1}$$

where TV denotes the total-variation operator, $G_x\{\cdot\}$ and $G_y\{\cdot\}$ are gradient operators along the rows and column of a 2D image, respectively, and $\odot$ denotes hadamard product. In Eq. (1), $term\ 1$ enforces consistency with the measurements, $term\ 2$ enforces minimum on the total variation of each image, and $term\ 3$ enforces similarity between the gradient images. The parameters $\lambda_{1,2}$ are regularization parameter that control the contribution of each term to the minimization problem, and $\mathbf{W}_{1,2}$ are weighting matrices that enhance the support estimation of the elements in $term 3$, updated iteratively as suggested by Candes et al. [7]. In our experimental results, we solved Eq. (1) by an extension of FISTA minimization approach, known as SFISTA [8].

III. Results

Our joint reconstruction approach has been tested on two different datasets: Purely synthetic phantoms representing T1 and T2 MRI contrasts and two imaging slices taken from two different MRI contrasts (T12 and T2) of the same subject. Data was undersampled randomly (using 4% of the samples for the phantom experiment and 20% of the samples for the real data experiment) in the k-space domain using polynomial variable density probability density function. Different random sampling patterns were generated for each image. For comparison purposes, we compared our joint reconstruction approach to TV-based reconstruction (i.e., solving Eq. (1) without $term\ 3$) [9]). To quantify the quality of image reconstruction, we computed the PSNR of each reconstruction, defined as: $20\log_{10}((1/N^2) \cdot \|\mathbf{X}_i - \hat{\mathbf{X}}_i\|_F)$ where $\hat{\mathbf{X}}_i$ and $\mathbf{X}_i$ represent reconstructed and fully sampled images, respectively.

Figures 1 and 2 show the results of the experiments. It can be seen that joint reconstruction outperforms conventional TV-based reconstruction, that does not exploit similarity in structures between images. Our aproach leads to an improvement of 1.8dB-3.7dB, and provides better recovery in regions with slow varying grey-levels and fine structures.

IV. Conclusion

In this paper we show the benefit in utilizing structural similarity between different MRI imaging contrasts, via adaptive weighted reconstruction. Future work will consist of examining the proposed approach on different medical imaging modalities (e.g. PET and CT).

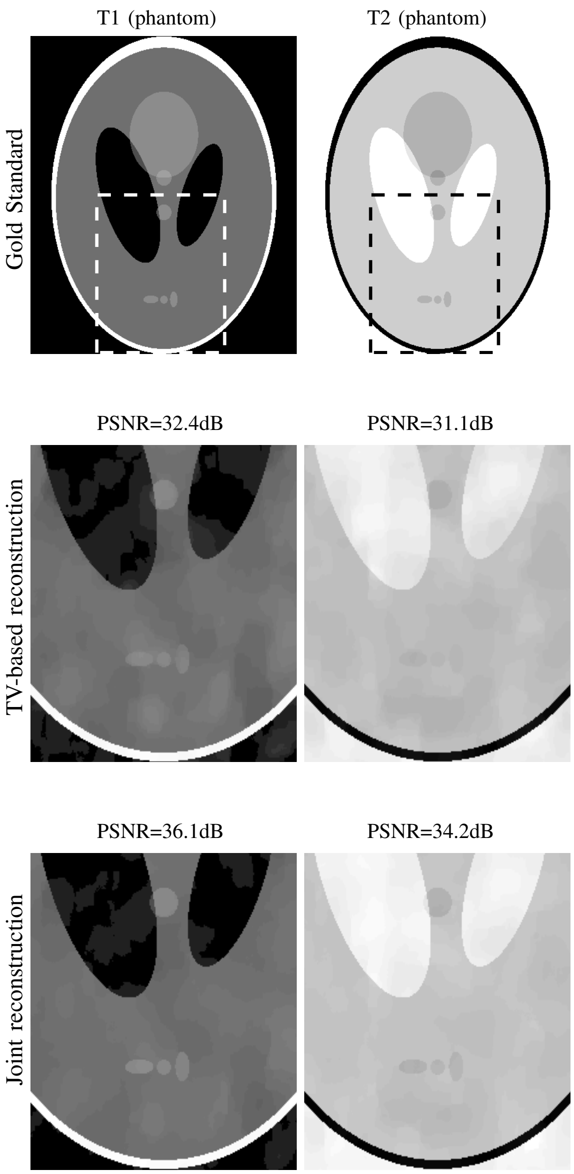

Fig. 1. Phantom results: Joint reconstruction vs. TV-based reconstruction. Gold standard T1 and T2 images are based on Shepp-logan phantom. Reconstruction results are shown in a zoomed region (the dashed rectangle on the gold standard). It can be seen that joint reconstruction outperforms TV-based reconstruction and exhibits much less imaging artifacts and improved PSNR values

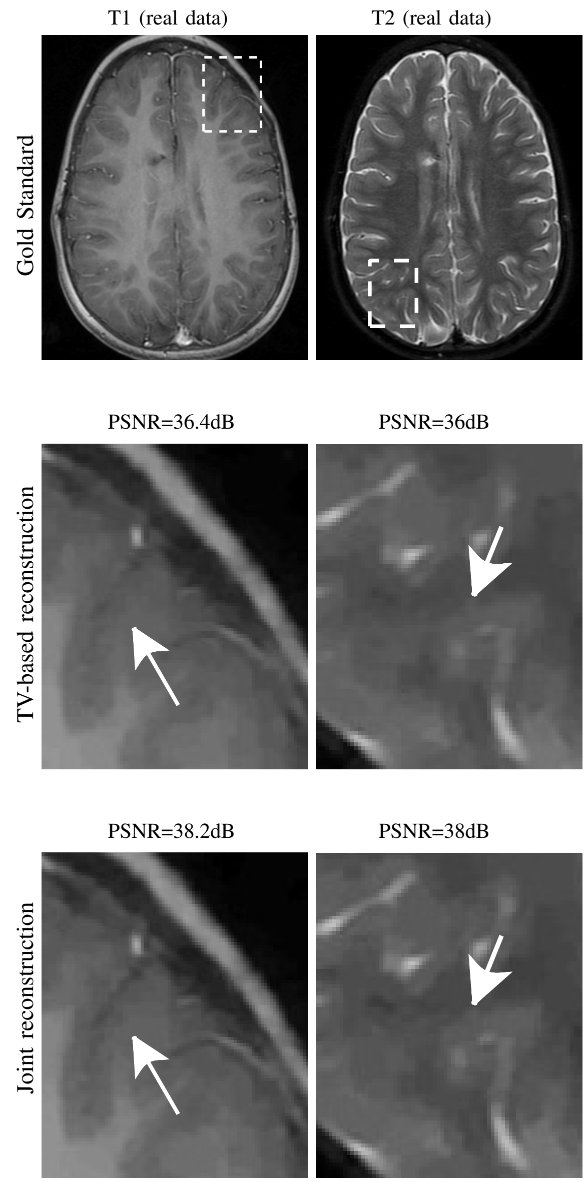

Fig. 2. Real data results: Joint reconstruction vs. TV-based reconstruction. Gold standard T1 and T2 images were taken from a clinical MRI study. Reconstruction results are shown in a zoomed region (the dashed rectangle on the gold standard). It can be seen that joint reconstruction exhibits better reconstruction of small scale structures (pointed by arrows) vs. TV-based reconstruction, and provides improved PSNR values

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