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 assume each MR image has a limited number of edges, that is, low total variation, but they are similar in the sense that many of the edges overlap. 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 significantly decrease the number of measurements required for successful reconstruction [3], in comparison to other compressed sensing [4], [5] based methods. However, when two MRI images are acquired in the same scan, we can benefit further by exploiting their similarity to reduce the sampling ratios [6]. As images of the same patient have similar spatial characteristics [7], 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 [8], [9]. We exploit the similarity between the gradients of the different imaging contrasts, on top of the well known total variation transform for each image. One of our novelties is the implementation via a re-weighting scheme. It improves support estimation [10] and allows handling cases where edges do not overlap, due to mis-registration or pathologies seen only in a single modality. 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 $\mathcal{F}_u : \mathbb{C}^{N\times N} \rightarrow \mathbb{C}^{1\times M}$ an undersampled Fourier transform, where $M < N^2$. In addition, we define: $\mathbf{X} = [\mathbf{X}_1, \mathbf{X}_2]$, $\mathbf{Y} = [\mathbf{y}_1, \mathbf{y}_2]$ and $\mathcal{F}_u\{\mathbf{X}\} = [\mathcal{F}_u\{\mathbf{X}_1\}, \mathcal{F}_u\{\mathbf{X}_1\}]$. We reconstruct X from Y by solving the following unconstrained problem:

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

where TV denotes the total-variation operator [11], $G_x\{\cdot\}$ and $G_y\{\cdot\}$ are gradient operators along the rows and column of a 2D image, respectively, and $\odot$ denotes the hadamard product. In (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, which expected to be similar since difference imaging contrasts exhibit similar structures. The parameters $\lambda_{1,2}$ are regularization parameters 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 [10]. The weighting scheme also helps in neglecting areas where edges in two different imaging contrasts do not overlap. In our experimental results, we solved Eq. (1) by SFISTA [12].

III. Results

Our joint reconstruction approach has been tested on purely synthetic phantoms representing T1 and T2 MRI contrasts and on two imaging slices taken from two different MRI contrasts (T1 and T2) of the same subject. Data was retrospectively undersampled randomly (using 4% and 20% of the samples for the phantom and the real data experiments respectively) 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) [11]. 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.

Figures 1 and 2 show the results. 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).

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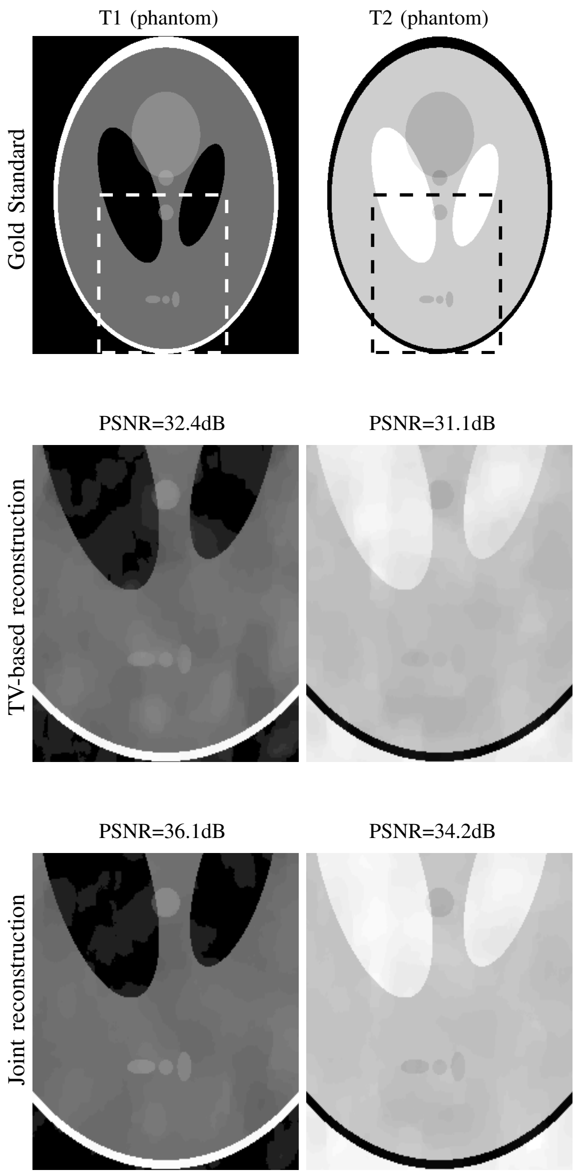

Fig. 1. Phantom results: Joint reconstruction vs. TV-based reconstruction. Gold standard T1 and T2 images are based on Shepp-logan phantom. Reconstruction results are shown in a zoomed region (the dashed rectangle on the gold standard). It can be seen that joint reconstruction outperforms TV-based reconstruction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

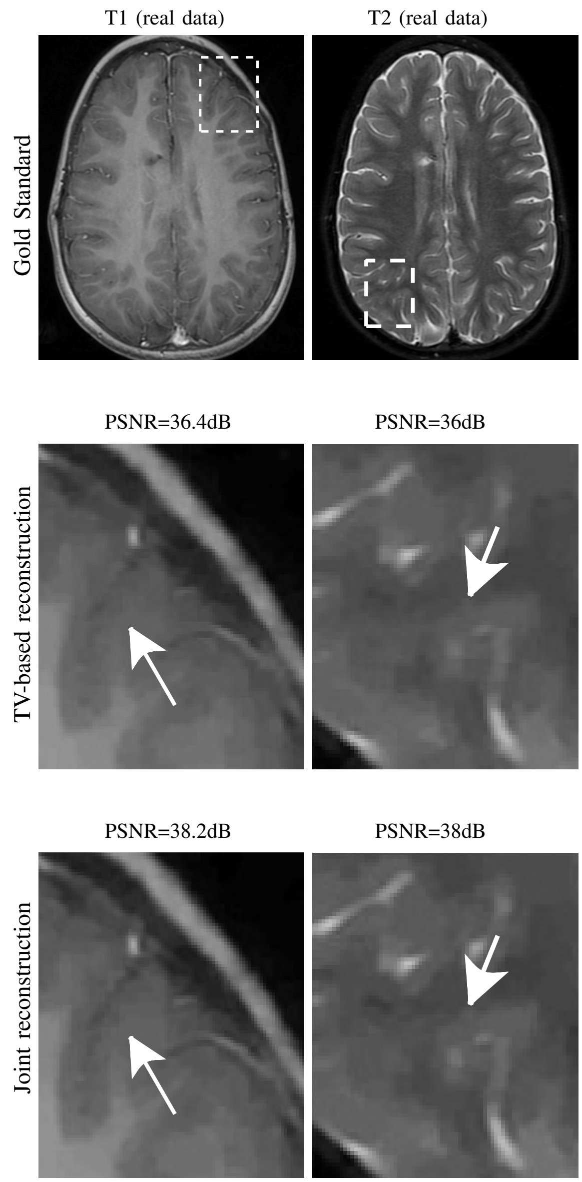

Fig. 2. Real data results: Joint reconstruction vs. TV-based reconstruction. Gold standard T1 and T2 images were taken from a clinical MRI study. Reconstruction results are shown in a zoomed region (the dashed rectangle on the gold standard). It can be seen that joint reconstruction exhibits better reconstruction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

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