User-guided Compressed Sensing for Magnetic Resonance Angiography

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***Abstract*— Compressed sensing (CS) magnetic resonance imaging (MRI) enables the reconstruction of MRI images with fewer samples in k-space. One requirement is that the acquired image has a sparse representation in a known transform domain. MR angiograms are already sparse in the image domain. They can be further sparsified through finite-differences. Therefore, it is a natural application for CS-MRI. However, low-contrast vessels are likely to disappear at high undersampling ratios, since the commonly used ℓ_1 reconstruction tends to underestimate the magnitude of the transformed sparse coefficients. These vessels, however, are likely to be clinically important for medical diagnosis. To avoid the fading of low-contrast vessels, we propose a user-guided CS MRI that is able to mitigate the reduction of vessel contrast within a region of interest (ROI). Simulations show that these low-contrast vessels can be well maintained via our method which results in higher local quality compared to conventional CS.**

I. INTRODUCTION

Compressed sensing (CS) magnetic resonance imaging (MRI) proposed by Lustig et al. [1] enables the fast reconstruction of images by using fewer measurements in k-space than conventional approaches. One important requirement for the application of CS MRI is that the underlying images should have a sparse representation in a known transform domain. Lustig et al. presented good reconstruction results for angiograms which have sparse representations in terms of finite-differences. Milles et al. [2] quantitatively evaluated the performance of CS MRI for time-of-flight (TOF) angiography but still observed the fading of low-contrast vessels in CS reconstructed results. For vessel diagnosis it is essential to reliably recognize and assess pathological abnormalities, such as narrowing (stenosis). Currently most of the vessel analysis requires segmentation of vessels as a pre-processing [3]. However, the fading or breaking of vessels could cause false positives in such diagnostic procedures. Therefore, in this paper, we propose a method aiming at the reconstruction of specific low-contrast vessels.

The fading is caused by the fact that ℓ_1 reconstruction employed in CS MRI shrinks the magnitude of the reconstructed sparse coefficients. This results in the reduction of image contrast especially at high undersampling ratios [1]. Then the desired boundaries between the low-contrast vessels and the background are more likely to fade or even vanish. To avoid these artifacts, we propose to add weights to the ℓ_1 reconstruction based on local information. Candes et al. [4] have already demonstrated the performance gain via weighted ℓ_1 minimization in areas of sparse signal recovery and image processing. Chang and Ji [5] extended the weighted ℓ_1 minimization to reconstruct multichannel in-vivo MRI data. Since ℓ_1 reconstruction works well for high-contrast vessels, we weight the ℓ_1 reconstruction for specific low-contrast vessels to maintain their boundary information.

There are several attempts to improve the quality of certain tissues (i.e., local quality) of the imaging object, which could be viewed as the region of interest (ROI), rather than the global reconstruction quality. Sharma et al. [6] managed to increase the image contrast within the ROI by only imposing the sparsity constraint outside ROI. However, the freedom in choosing the size of ROI is limited. For large ROIs, their method would turn into an ill-posed least-squares problem. Oh and Lee [7] derived the visual weight by incorporating ROI and perceptual characteristics of the human visual system. They masked the underlying image, which became the reconstruction target. But this method could reduce to an ill-posed problem if the ROI is really small such as in the case of angiography. In this paper, there are no limitations about the size of the ROI which could either be the entire image or empty.

Our proposed method first defines the ROI where low-contrast vessels are located. Then the weights are generated based on the gradient information within ROI. The final image is reconstructed via the weighted ℓ_1 reconstruction. The method was evaluated on two TOF angiography scans.

II. METHODOLOGY

The pipeline of the proposed method is illustrated in Fig. 1. The partially measured k-space data and an initial image data serve as the input. The initial image is used to define the ROI by the users (e.g., radiologists) via semi-automatic or interactive segmentation. These ROI contain low-contrast vessels which cannot be well maintained via conventional CS. The ROI does not need to be precisely defined, and a rough estimation is enough. The initial image can either be a zero-filling image or a conventional CS reconstructed image. In this paper, we choose to use the conventional CS reconstructed images with fewer iterations. The weights are generated based on the gradient information within the ROI. The final images are reconstructed via weights-incorporated ℓ_1 reconstruction. In the following we will describe weights construction and weighted CS reconstruction in more detail.

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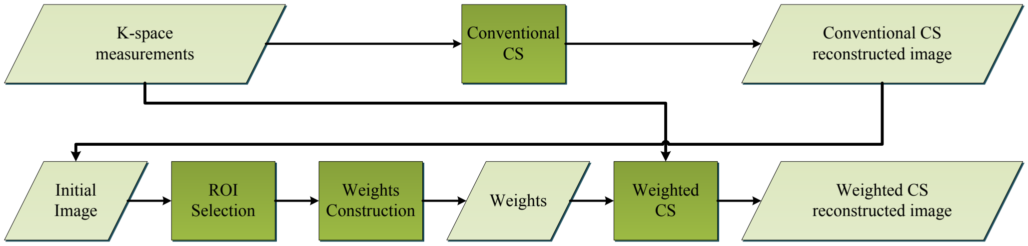


Fig. 1. The weighted CS reconstruction pipeline

A. ROI-based weights construction

The primary information of angiograms consists of blood vessels from which we derive clinically-related parameters such as the diameters and length of vessels. The boundaries are of special relevance for these parameters. They can be estimated by calculating the gradient in the initial image using central differences. We do not choose a smoothed derivative filter, such as the Gaussian derivative filter, in order to capture small scale vessel features. User-defined ROI is applied to mask the gradients, which are normalized to the range between 0 and 1 by the maximum gradient magnitude. The weights are constructed by reversing the normalized gradients:

$$M_{i,j} = \left\|\nabla I_{i,j}\right\| \cdot ROI_{i,j}$$

$$W_{i,j} = 1 - \frac{M_{i,j}}{\max\left(M_{i,j}\right) + \varepsilon}$$

Here I is the initial image, ∇ is gradient operator, ROI is the binary mask, M is the gradient magnitude within the ROI, ε is a very small number preventing the division by 0 and W is the generated weights.

B. CS Reconstruction using ROI weight

Lustig et al. [1] presented the reconstruction of angiograms using finite-differences as the sparsifying transform, which is referred as total-variation (TV) minimization. Besides, unlike the Fourier transform, finite-difference provides spatially local information and has low computational complexity compared to other sparse transforms such as wavelet. We also employ TV minimization to reconstruct the original angiograms. The reconstruction are performed by solving the following optimization problem:

$$\arg\min_{m} \|F_u m - y\|_2 + \lambda \|m\|_{TV}$$

$$\|m\|_{TV} = \sum_{i,j} \|(Dm)_{i,j}\|_1$$

where m is the desired image, F_u is randomly-sampled Fourier operator, y are the k-space measurements, D represents the forward differences operator and λ is the regularization parameter that determines the trade-off between data consistency and TV regularization. The ℓ_2 norm is defined as $\|x\|_2 = \left(\sum_i |x_i|^2\right)^{1/2}$ while the ℓ_1 norm as $\|x\|_1 = \sum_i |x_i|$.

Fig. 2(a) shows the fully sampled 3D angiography which will be used as the ground truth. Fig. 2(b) is the color-coded initial image reconstructed by conventional CS. Both are under the same rendering settings, and we can clearly observe the breaking and fading of vessels marked in three white polygons. These regions containing these vessels are selected as ROI. Fig. 2(c) shows one slice of the generated weights overlapped with CS reconstructed data. The weights are color-coded by perceptually linear yellow-to-blue colormap. Yellow represents low weights while blue the high weights. Transparency represents the highest weights (i.e., 1.0) for areas outside of the ROI.

The TV term penalizes intensity variations. This penalization, however, shrinks the magnitude of the transform coefficients resulting in a reduction of image contrast. The desired boundaries are likely to fade or even vanish. Therefore, we propose to add weights to the TV minimization. Voxels inside the ROI with relatively high gradients are candidates for boundaries. The weights should be relatively low for these voxels and vice versa. This means, within the ROI, intensity variations for boundary candidates can be tolerated. The proposed optimization problem is:

$$\arg\min_{m} \|F_u m - y\|_2 + \lambda \|m\|_{wTV}$$

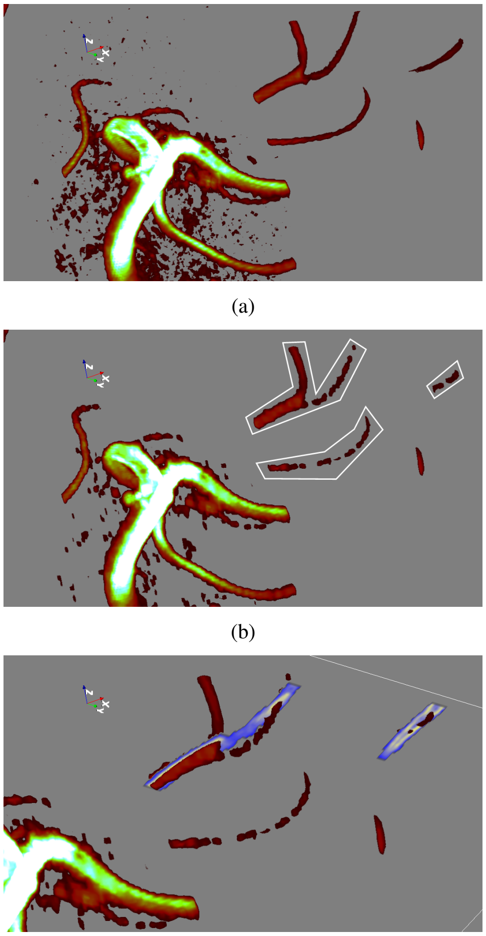
$$\|m\|_{wTV} = \sum_{i,j} W_{i,j} \|(Dm)_{i,j}\|_1$$

where $W_{i,j}$ are the derived voxel-wise weights in the range of $[0,1]$.

III. RESULTS

We simulated k-space data by computing the Fourier transform of a volume (56 slices) of a high resolution 3DFT TOF angiogram with a voxel-size of 0.23 mm $\times$ 0.23mm $\times$ 0.35mm. We also used the fully sampled k-space data of a volume (32 slices) of a low resolution DFT TOF angiogram with a voxel-size of 1mm $\times$ 1mm $\times$ 1mm. From the full k-space data, five under-sampled data sets with corresponding sampling ratios of 10%, 15%, 20%, 25% and 30% were reconstructed.

We compared our methods qualitatively and quantitatively with Lustig's method (conventional CS) [1] and the fully sampled data set. The normalized mean squared errors (NMSE) is used to evaluate the *local* performance within the ROI.



(a)

(b)

(c)

Fig. 2. ROI-based weights construction. (a) fully sampled 3D angiogram; (b) CS reconstructed angiogram with sampling ratio of 10%; (c) a close-up of the generated weights overlaid with CS reconstructed angiogram.

Maximum Intensity Projections (MIP) are frequently used by clinical users for the visualization of vascular structures. Often a threshold is used to eliminate noisy background and the visualization of low intensities. For small vessels, if their intensities are low in certain regions, this threshold might generate breaks and discontinuities. We used the masks resulting from several thresholds to evaluate the reconstruction results and compared them with the ground truth. Dice Coefficients (DC) are thus used as an extra metric for comparison.

A. DISCUSSION

As shown in Table I, the ROI-based NMSEs for our method are consistently lower than for conventional CS. DCs, as a function of sampling ratios, are shown in Fig. 3 (right) at a threshold 10% of the maximum intensity while Fig. 3 (left) shows DCs when varying the thresholds with constant sampling ratio of 20%. The DCs derived from our method are consistently higher especially at low sampling ratios. With low thresholds, both show high values because the background voxels are segmented as vessels which are shown in Fig. 4(a). As increasing the thresholds, more background voxels are removed. But the DC for our method declines slower than for conventional CS which are visually reflected in Fig. 4(b). The above evaluation results demonstrate that our method can better maintain the intensity connectivity of vessels.

TABLE I

ROI NMSE OF THE HIGH RESOLUTION TOF ANGIOGRAM WITH VARIOUS SAMPLING RATIOS

	10%	15%	20%	25%	30%
conventional CS	0.0471	0.0315	0.0241	0.0185	0.0140
ROI-based CS	0.0456	0.0288	0.0208	0.0156	0.0118

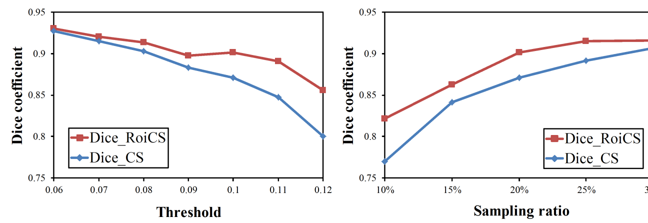


Fig. 3. ROI-based Dice Coefficient comparison. Left: DC variations with different thresholds under the same sampling ratios (20%); Right: DC variations under different sampling ratios at fixed threshold (10%).

The ROI-based NMSE for the low resolution angiogram are shown in Table II. As shown in Fig. 5 (top), the vessels contained in the white polygons (i.e., ROI) are marked as the specific reconstruction target. From the close-up views in Fig. 5 (middle and bottom), it can be observed that our method can maintain the intensity connectivity better in most areas. The reason why we do not include DC in this experiment is that even for the fully sampled data set, the vessels within the ROI can not be segmented merely based on the thresholds.

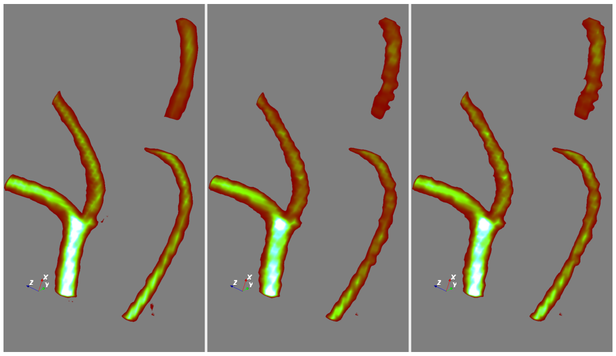
TABLE II

ROI NMSE OF THE LOW RESOLUTION TOF ANGIOGRAM WITH VARIOUS SAMPLING RATIOS

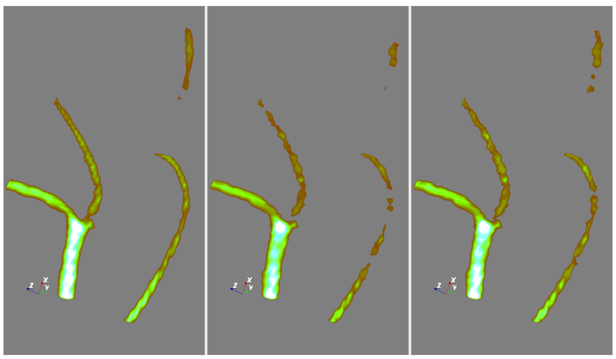
	10%	15%	20%	25%	30%
conventional CS	0.1628	0.0870	0.0506	0.0366	0.0280
ROI-based CS	0.0999	0.0562	0.0362	0.0256	0.0207

The difference of *overall* NMSE between our method and the conventional CS are small. This is due the fact that the vessels within ROI normally occupy a relatively small part of total voxels.

The method we propose does not suffer from the limitations in ROI selection as in [6]. If the selected ROI is empty, the optimization function converges with conventional CS. If the selected ROI is the entire image, our reconstruction function just tolerates the intensity variations for voxels with globally large gradient magnitudes rather than reduce to an ill-posed problem. Our method is sensitive to the ROI definition. However, as long as within the region there are no high differences in the gradient magnitude the method will work. Furthermore, our method is not suitable for enhancing



(a) MIP renderings with threshold at 6% the maximum intensity



(b) MIP renderings with threshold at 10% the maximum intensity

Fig. 4. MIP renderings of the original high-resolution angiogram (left), the conventional CS (middle), our method (right). Sampling ratio is 20%.

very weak vessels because the derived gradient magnitude is extremely small which will lead to high weights for the subsequent reconstruction.

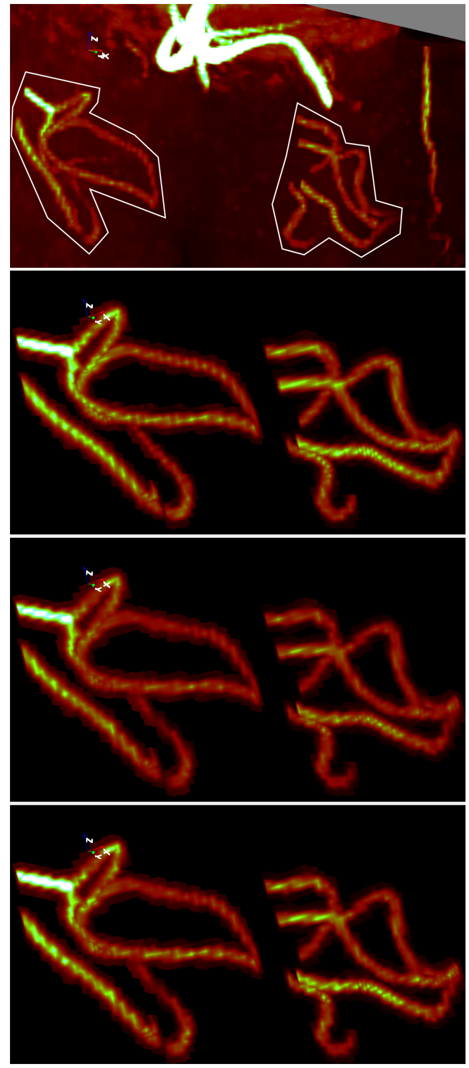


Fig. 5. MIP renderings for the low-resolution angiography. Top: the overview of conventional CS, the close-up views of the original (middle-top), conventional CS (middle-bottom) and our method (bottom). Sampling ratio is 20%.

IV. CONCLUSIONS AND FUTURE WORK

CS MRI is able to reconstruct the angiograms from an incompletely sampled k-space. However, low-contrast vessels are likely to fade at high undersampling ratios. To mitigate this, we proposed a weighted CS reconstruction which considers user-annotated ROIs containing low-contrast vessels. Low weights correspond to high gradients which means that intensity variations can be tolerated at vessel boundaries. Preliminary results show that our method using both simulated and clinically acquired k-space data can maintain the intensity connectivity for ROI-based low-contrast vessels better than the conventional CS.

However, there are still several topics for future work. We construct the weights from the initial image and keep it constant for the reconstruction. Weights can be adaptively constructed and tuned after each reconstruction iteration. Furthermore, a more extensive evaluation with more data sets and clinically relevant parameters is necessary to show the real applicability of the proposed method in clinic.

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