Non-Contrast-Enhanced 4D MRA Using Compressed Sensing Reconstruction

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Introduction : In the recent years, non-contrast magnetic resonance angiography (NCE MRA) has been an emerging tool in the diagnosis of degenerative vascular disease [1]. In this context, a novel time-resolved data acquisition method was proposed [2]. This technique uses two ECG-triggered CINE-like b-SSFP acquisitions of multiple 3D phases: One after selective and another one after non-selective inversion. With a subtraction of the two datasets, the background signal can be eliminated, and the difference between the signals of differently labeled inflowing blood yields time-resolved vascular information. Desired improvements include a reduction of the total scan time to reduce the impact of unintentional motion as well as an increase of the spatial and/or temporal resolution. Thus, the compressed sensing (CS) technique, which aims at reconstructing high quality signal from largely undersampled acquisitions, is a natural fit to further enhance time-resolved NCE-MRA applications.

Methods: Given the assumption that the image to be reconstructed is sparse or can be sparsified by some transformations, compressed sensing theory shows that the sparsest solution to the following L1-L2 minimization problem recovers the true image with high probability

$$\arg\min_f \{\| \varphi(f) \|_1\} \qquad s.t. \quad \| Af - y \|_2 \le \varepsilon, \tag{1}$$

where f is a trial image; φ is a sparsifying transformation; y is the measured k-space data; **A** is an encoding matrix that maps the image into k-space; and ε is a parameter that accounts for deviation between the measurement and ideal data. In the current application of Cartesian 4D NCE-MRA, the Karhunen-Loeve transform (KLT) is applied in the temporal dimension to obtain the sparse representation; **A** is simply a subsampled Fourier matrix; and Eq. (1) is solved by NESTA with the reweighted L1 scheme [2]. In a nut shell, the KLT first finds the principle components which are the eigen-vectors of the signal covariance matrix, and then projects the signal onto these vectors to obtain decomposition coefficients. The major principle axis corresponds to the direction that the coefficients along this direction has the largest variance. Therefore in our case, most sparse bright vessels in the images would be represented (after the KLT) as a few large coefficients in the major principle component; and most artifacts and noise would result in smaller coefficients distributed in those components other than the major one. These artifacts and noise are then suppressed while the objective function is minimized; and the true structures are preserved while the constraint is satisfied in Eq. (1).

Results: With the acquisition scheme described in [2], 4D NCE-MRA data were acquired in healthy volunteers on a 3.0T clinical MR scanner (Magnetom Trio a Tim System, Siemens AG). The data size was 112x84x30x13x2x4, where the numbers denote, in order, height, width, partition, phase, repetition (i.e. two different labelings), and coil channel number. In our reconstruction procedure, we first subtract the two repetitions in k-space to obtain a supposedly "vessel-only" representation. For demonstrative reasons we restricted the reconstruction to two spatial dimension and the temporal dimension at a time and applied it separately for each partition and each channel. This means that the dimension of f as in Eq. (1) was 112x84x13; and a total of 30x4 reconstructions needed to be performed. The 4 independent receiver channels were afterwards combined as the sum of squares. To model random sampling as suggested by the CS theory, we started with a fully sampled data (112 phase encoding lines) for each frame, and select 14 lines (8x acceleration) for reconstruction. Specifically, 7 out of the 14 lines are chosen to fill the k-space center, while the remaining 7 were uniformly and randomly distributed in remaining k-space. Our experimental results, which were obtained by maximum intensity projection (MIP) to the transverse plane for the 10th phase, are shown in Fig. 1 for the different reconstruction approaches. Please refer to the figure caption for the corresponding image reconstruction methods. Fig. 1(a) illustrates the severe aliasing artifacts when we directly applied the Fourier transform to the undersampled data with zero-filling. Comparing with the ground truth in Fig. 1(e), Fig. 1(b) has higher noise level, missing details, lower quality vessels, and residual aliasing artifacts, as indicated by, respectively, the dashed ellipse, the solid arrows, the dashed square, and the dashed arrow. It is clear that in Fig. 1(c) the residual aliasing artifacts are still dominant and many details are missing. Fig. 1(d) is the proposed result that achieves comparable visual image quality as that of the ground truth, which is shown in Fig. 1(e). Quantitatively, we computed the mean squared error (MSE) between the energy-normalized reconstructed 4D volume (size 112x84x30x13) and the ground truth, and divide it by the energy of the ground truth to obtain the relative MSE (rMSE). The rMSE for the methods (a)~(d) are, respectively, 3.47, 0.72, 1.66, 0.47, which correspond well with the visual quality and also justify the use of the KLT. Note that the rMSE only gives a relative quality measure because the ground truth is fully sampled so that its energy is essentially different from the undersampled reconstruction.

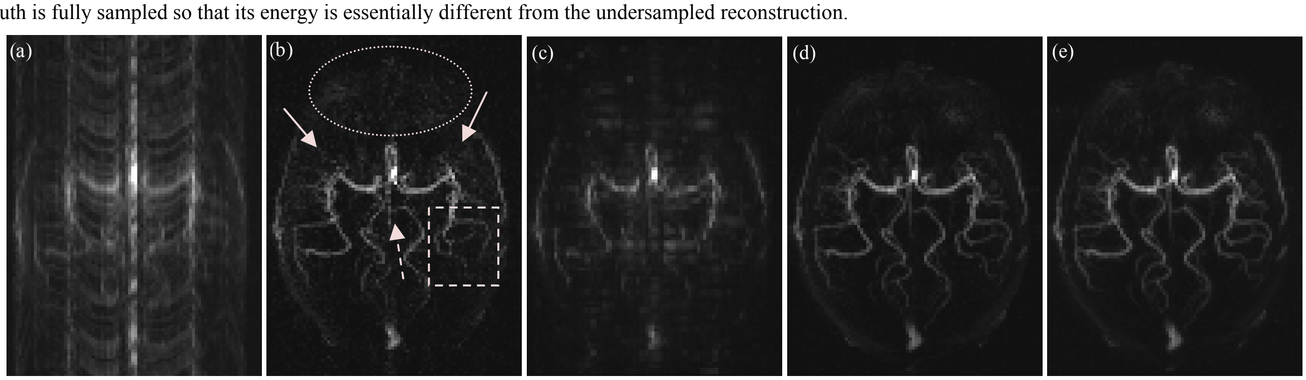

Fig. 1: MIP images showing reconstruction by (a) the Fourier transform with zero-filling, (b) no sparsifying transform in Eq. (1), i.e., φ is the identity mapping, (c) setting φ to be the Daubechies-8 wavelet spatial transform, (d) setting φ to be the KLT which is applied in the temporal dimension, and (e) the Fourier transform with the fully sampled data, i.e., the ground truth. These methods are also referred to as (a), (b), (c), (d), and (e) in the text above.

Discussion and Conclusion: The novel technique introduced in [2] represents a promising approach for time-resolved 4D NCE-MRA. In current work, it was demonstrated that further improvements in spatial/temporal resolution or a reduction in acquisition time are feasible by CS reconstruction from undersampled acquisitions. By subtracting the two differently spin-labeled datasets in k-space, it was possible to work on images with vascular structures only, i.e. images that are sparse in the image domain. To further sparsify the data and facilitate CS framework, the KLT was applied in the temporal dimension. Finally, a state-of-the-art solver was adopted for the L1-L2 minimization problem. Our results show that results comparable to the ground truth can be achieved at 8-fold acceleration. A natural extension of our current work is to add algorithms that exploit the spatial sensitivity information of the multiple coil elements and to perform a true 4D reconstruction in order to achieve even higher acceleration rates.

References: [1] M. Miyazaki and V. S. Lee, Radiology 248(1):20-43 (2008). [2] X. Bi *et al.*, Proc Intl Soc Mag Reson Med 17, #3259 (2009). [3] S. Becker *et al.*, arXiv :0904.3367 [math.OC] (2009)