

Kiosk 11R-TB-10

## Motion-robust 3D Cine Imaging Using Compressive Recovery with Outlier Rejection (CORe)

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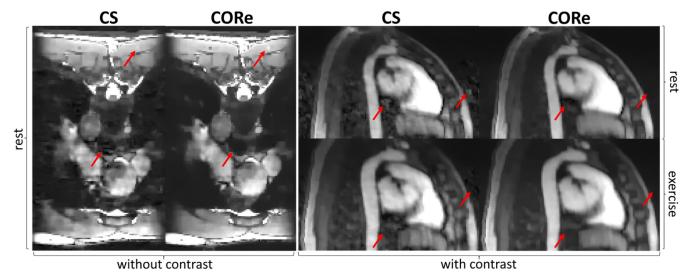
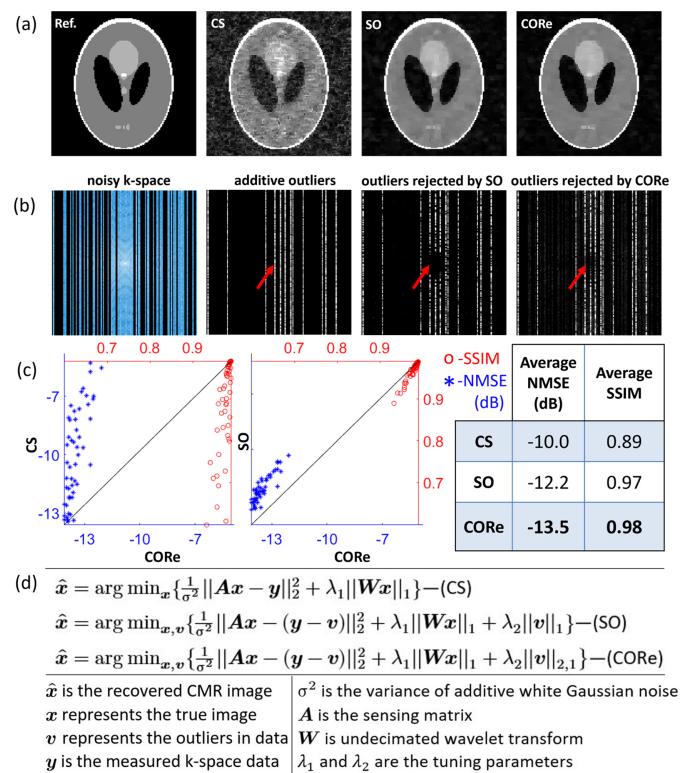
**Background:** Free-breathing self-gated 3D cine imaging offers several advantages over multi-slice 2D cine imaging. The quality of the 3D imaging, however, depends on the reliability of the extracted respiratory motion signal. Typically, the extracted respiratory motion signal is not perfect, leading to misplacement of some of the k-space data into incorrect respiratory bins, and, in turn, motion artifacts. This problem becomes more pronounced in exercise stress imaging, which is emerging as a modality to identify functional impairments that may not be evident at rest. We propose a method called Compressive recovery with Outlier Rejection (CORe), which provides motion-robust reconstruction by suppressing the impact of misplaced data, called outliers.

**Methods:** We compared CORe with standard compressed sensing (CS) and the outlier rejection method proposed by Dong et al. (2012), termed sparse outliers (SO).<sup>1</sup> These reconstruction methods can be formulated as optimization problems presented in Figure 1d. CORe explicitly models the outliers using an auxiliary variable  $v$  and leverages the structure in the MRI data to impose sparsity on outliers at a group (readout) level using the term  $\lambda_2\|v\|_{1,2}$ . We performed a simulation study using the k-space data of Shepp-Logan phantom, which was retrospectively undersampled at an acceleration rate of 2.4 using Cartesian sampling and polluted with additive circularly symmetric white Gaussian noise. To simulate motion-corrupted outliers, a fraction of the sampled readouts was polluted with additional noise of much larger variance. This experiment was repeated for 50 realizations, each with a random sampling pattern, outlier locations in k-space, and the outlier fraction that ranged from 1% to 20% of the sampled readouts. For in-vivo evaluation, we compared CORe with CS reconstructions of seven high-resolution 3D cine datasets, six acquired at rest and one during exercise. The scan parameters and subject details are summarized in Table 1. The comparison was made through a blinded scoring on a scale of 1 (worst) to 5 (best) by three CMR experts on two criteria: artifacts and image sharpness.

**Results:** Figure 1 summarizes the results of the phantom study. On average, CORe outperforms CS and SO methods in terms of NMSE and SSIM of reconstructed images. Furthermore, Figure 1b highlights the advantage of using group sparsity in CORe, as SO is unable to eliminate the entire readout (outlier). The overall results of the reader study, illustrated in Table 1, indicate that CORe is more effective than CS in reducing artifacts while preserving image sharpness; this can be observed visually from the representative images shown in Figure 2.

**Conclusion:** In conclusion, the proposed method, CORe, integrates outlier rejection into the reconstruction framework. Data from a Shepp-Logan phantom and 3D rest and exercise stress cine imaging demonstrate that CORe is more effective in suppressing motion

artifacts than traditional CS techniques.



**Table 1: Imaging Parameters & Results of a Blinded-reader Study**

### 3D cine study parameters

Total datasets	7
Field strength	5 at 1.5T, 2 at 3T
Subject details	age range: 23-75; 3 patients; 2 with ferumoxytol; 1 female
TE/TR (ms)	1.2-1.5/3.1-3.3
FOV (mm <sup>3</sup> )	240 × 240 × 52-440 × 440 × 144
Spatial resolution (mm <sup>3</sup> )	1.0 × 1.3 × 1.0-2.1 × 2.3 × 2.1
Temporal resolution (ms)	24-50
Sequence	3 × bSSFP, 4 × GRE
Acceleration rate	7-34
Flip angle (degrees)	33-60 bSSFP, 12-14 GRE
Acquisition time (min)	4-5

Blinded-reader study			
Dataset	Artifacts	Sharpness	CORE
1	2.7	4.0	3.3
2	4.3	4.7	3.7
3	3.3	4.0	2.7
4	4.3	4.7	3.3
5	3.0	3.7	1.7
6	2.7	3.7	2.0
7	2.7	4.0	2.0
Average	3.3	4.1	2.7
			3.0

**Author Disclosure:** S Arshad: Nothing to disclose; L Potter: N/A; C Chen: N/A; P Chandrasekaran: N/A; Y Liu: N/A; C Crabtree: N/A; M Tong: N/A; O Simonetti: N/A; Y Han: N/A; R Ahmad: N/A

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Non-rigid Motion Corrected Reconstruction with Nonlocally Low-rank Tensor Decomposition Based Regularization for High-resolution Cartesian First-pass Myocardial Perfusion Imaging at 3 Tesla

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**Background:** First-pass myocardial perfusion imaging is important for evaluating ischemic heart disease<sup>1</sup>. As images are typically acquired over 60 heartbeats<sup>2</sup>, breath-holding is difficult and respiratory motion is unavoidable. Motion disrupts the temporal consistency, compromising reconstructions exploiting temporal correlation. Furthermore, motion correction is essential for accurate voxel-wise quantification. The contrast variation during perfusion and residual aliasing of undersampled images make non-rigid motion-corrected reconstruction challenging<sup>3</sup>. This work aims to correct the non-rigid motion by obtaining the deformation fields from the undersampled data via auxiliary reconstruction, and then incorporating the motion information into the forward model to facilitate a joint sparsity and low-rank constrained tensor decomposition<sup>4</sup> based reconstruction (TDLLS-MOCO) at acceleration rate (R) of 4-6.

**Methods:** Figure 1 shows the pipeline for the TDLLS-MOCO reconstruction. Resting first-pass perfusion images were acquired in 5 patients undergoing clinical CMR studies with gadolinium on a 3T scanner using a pulse sequence with the following parameters: GRE readout, resolution 2 x 2mm<sup>2</sup>, slice thickness 8mm, R=2. The datasets were retrospectively undersampled with R = 4 and R = 6 using the GRO sampling pattern<sup>5</sup>. Reconstruction were compared to SENSE reconstruction<sup>6</sup> with deformation in the forward model (SENSE-MOCO), L2-norm regularized subspace reconstruction<sup>7</sup> (subspace-MOCO) and the locally low-rank regularized subspace reconstruction<sup>8</sup> (LLR-MOCO). Images were compared visually on a 5-point scale (1 poor to 5 excellent) by a cardiologist. Temporal fidelity was assessed in the ventricular cavities.

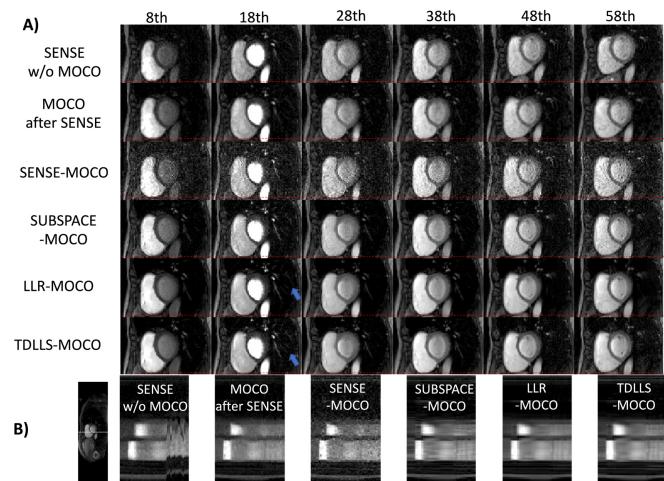
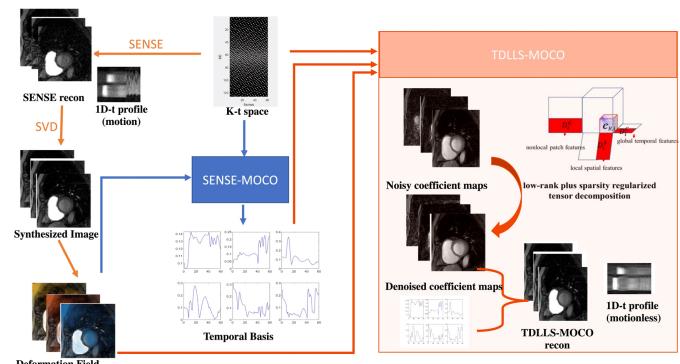
**Results:** Figure 2A shows perfusion images from a patient with substantial respiratory motion at R = 4. The later frames are well aligned after motion correction (Fig 2B). Compared with the SENSE-MOCO and the MOCO after SENSE reconstruction, the blurring effect is reduced by incorporating the motion field into the forward model. By applying temporal basis (subspace-MOCO, LLR-MOCO, TDLLS-MOCO), the noise and artifacts are substantially reduced. The proposed TDLLS-MOCO reconstruction shows further improved image quality with clear depiction of small tissues.

Figure 3 shows the performance of TDLLS-MOCO at R = 4 and R = 6. The TDLLS-MOCO images are well aligned with improved

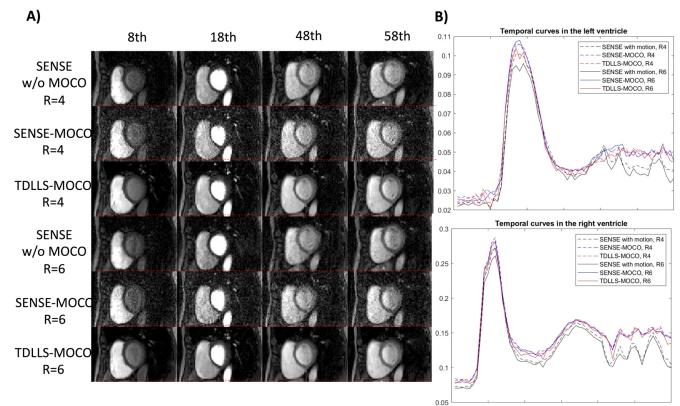
image quality and high temporal fidelity as compared to SENSE and SENSE-MOCO.

The average image quality scores for the SENSE without MOCO, SENSE-MOCO and TDLLS-MOCO were 3.4, 3.8, 4.6, respectively.

**Conclusion:** By jointly incorporating the nonrigid motion correction and the sparsity and low-rank regularized tensor decomposition into the reconstruction, motion-corrected perfusion imaging with substantially improved image quality compared with SENSE, subspace and LLR reconstructions could be achieved at a high acceleration of 6 for the 2D Cartesian perfusion imaging using the propose TDLLS-MOCO pipeline.



**B)** SENSE w/o MOCO, MOCO after SENSE, SENSE-MOCO, SUBSPACE-MOCO, LLR-MOCO, TDLLS-MOCO



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