Motion-robust free-running cardiovascular MRI

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INTRODUCTION

In free-breathing Cardiovascular Magnetic Resonance (CMR) imaging, retrospective self-gating is typically used to account for respiratory motion.[1] The quality of the 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.[2] CORe reconstruction model entails solving the optimization problem illustrated in Figure 1.

METHODS

We compared CORe with standard compressed sensing (CS)[3], robust regression (RR) method[4] and the outlier rejection method proposed by Dong et al. (2012), termed sparse outliers (SO).[5] These reconstruction methods can be formulated as optimization problems presented in Figure 1. CORe explicitly models the outliers using an auxiliary variable $\boldsymbol{v}$ and leverages the structure in the MRI data to impose sparsity on outliers at a group (readout) level using the term $\lambda_2||\boldsymbol{v}||_{2,1}$.

CMR reconstruction methods

Compressed Sensing (CS):	$\hat{\boldsymbol{x}} = \arg\min_{\boldsymbol{x}} \left\{\frac{1}{\sigma^2}\|\|\boldsymbol{A}\boldsymbol{x}-\boldsymbol{y}\|\|_2^2 + \lambda_1\|\|\boldsymbol{W}\boldsymbol{x}\|\|_1\right\}$
Robust Regression (RR):	$\hat{\boldsymbol{x}} = \arg\min_{\boldsymbol{x}} \left\{\frac{1}{\sigma^2}\|\|\boldsymbol{A}\boldsymbol{x}-\boldsymbol{y}\|\|_1^1 + \lambda_1\|\|\boldsymbol{W}\boldsymbol{x}\|\|_1\right\}$
Sparse Outliers (SO):	$\hat{\boldsymbol{x}} = \arg\min_{\boldsymbol{x},\boldsymbol{v}} \left\{\frac{1}{\sigma^2}\|\|\boldsymbol{A}\boldsymbol{x}-(\boldsymbol{y}-\boldsymbol{v})\|\|_2^2 + \lambda_1\|\|\boldsymbol{W}\boldsymbol{x}\|\|_1 + \lambda_2\|\|\boldsymbol{v}\|\|_1\right\}$
Compressive recovery with Outlier Rejection (CORe):	$\hat{\boldsymbol{x}} = \arg\min_{\boldsymbol{x},\boldsymbol{v}} \left\{\frac{1}{\sigma^2}\|\|\boldsymbol{A}\boldsymbol{x}-(\boldsymbol{y}-\boldsymbol{v})\|\|_2^2 + \lambda_1\|\|\boldsymbol{W}\boldsymbol{x}\|\|_1 + \lambda_2\|\|\boldsymbol{v}\|\|_{2,1}\right\}$ Proposed method

$\hat{\boldsymbol{x}}$ is the recovered CMR image
$\boldsymbol{x}$ represents the true image
$\boldsymbol{v}$ represents the outliers in data
$\boldsymbol{y}$ is the measured k-space data
σ^2 is the variance of white Gaussian noise
$\boldsymbol{A}$ is the sensing matrix
$\boldsymbol{W}$ is undecimated wavelet transform
λ_1 and λ_2 are the tuning parameters

Figure 1 Reconstruction methods formulated as optimization models for accelerated CMR imaging.

Phantom simulation study:

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 added circularly symmetric additive white Gaussian noise. To simulate motion corrupted readouts, a fraction ranging from 1% to 20% of the sampled readouts were polluted with additional noise of much larger variance. This experiment was repeated for 50 realizations, each with a random sampling pattern and varying fraction and location of outliers in k-space.

3D cine in-vivo study:

For 3D cine imaging in-vivo evaluation, we compared CORe with CS for reconstruction of seven (four patients and three healthy subjects) high resolution 3D cine datasets, six acquired at rest condition and one during exercise on 1.5T and 3T clinical scanners. The comparison was made through a blinded reader study in which three CMR experts scored seven pairs of images from each dataset on two criteria: image sharpness and artifact reduction. Scoring was performed on a five-point scale with a score of 1 indicating non-diagnostic quality and a score of 5 representing a high-quality image.

Rest and stress 4D flow in-vivo study:

We compared CS and CORe for reconstruction of twelve 4D flow datasets—six collected at rest state and six acquired during exercise stress. To compare blood flow quantification at rest using CORe and CS, real-time 2D phase-contrast MRI (2D-PC) was collected as a reference. Aortic net flow quantification over a cardiac cycle was compared using 2D-PC, CORe, and CS. To assess the efficacy of CORe in mitigating motion artifacts compared to CS in stress 4D flow imaging, we evaluated mean and standard deviation (SD) of net flow across five ascending aorta (Aao) transecting planes. These planes were defined to ensure consistent physiological flow, allowing for a comprehensive comparison.

2D Shepp-Logan phantom simulation study

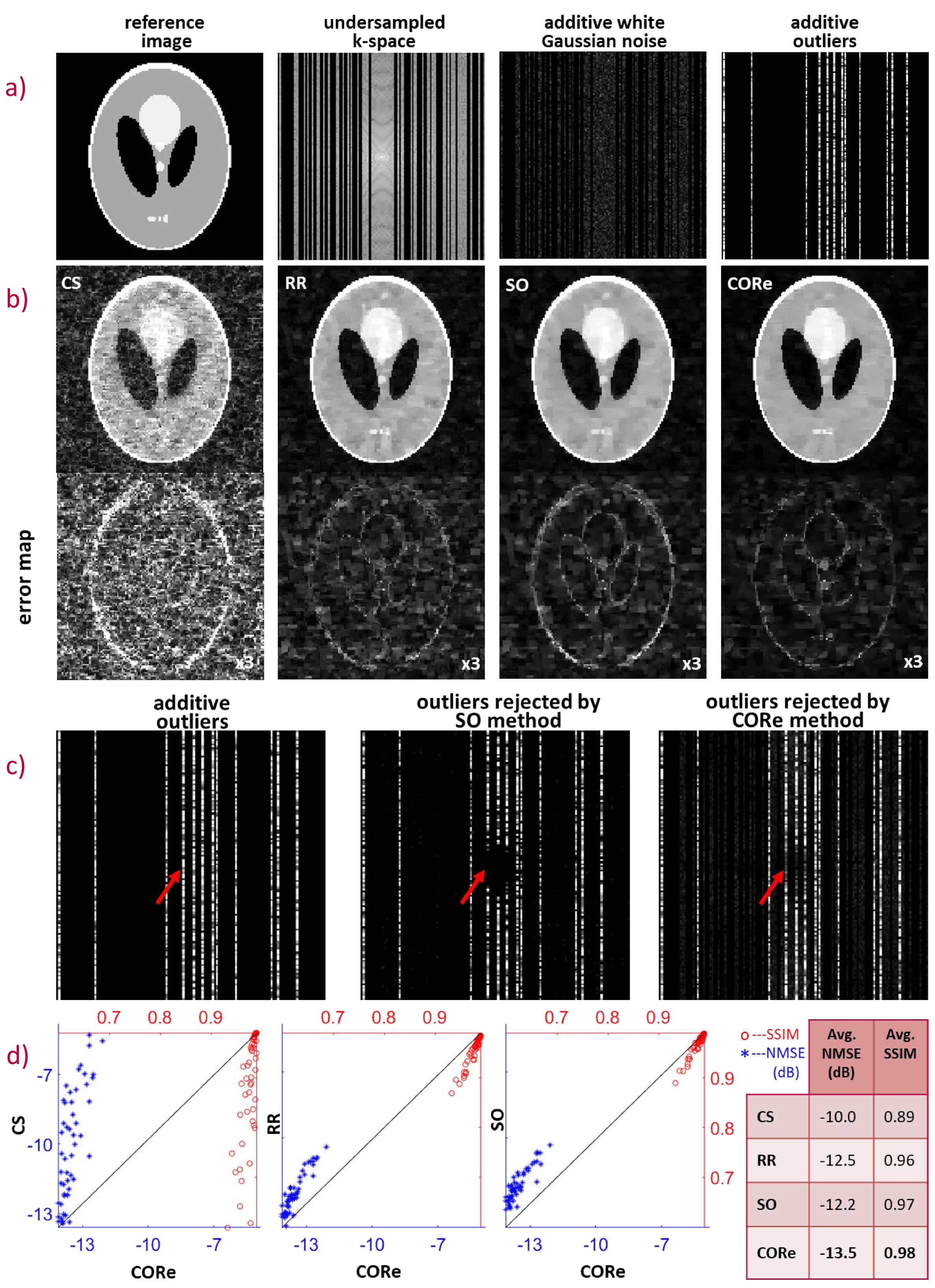

Figure 2 Summary of results from Shepp-Logan phantom study. (a) displays the reference image, undersampled k-space measurements, additive white Gaussian noise and additive outliers for a representative realization. (b) shows reconstructed images using CS, RR, SO, and CORe and the corresponding error maps amplified by a factor of 3, for the realization shown in (a). (c) compares outliers rejected by SO and CORe for the images reconstructed in (b). (d) compares CORe with CS, RR and SO, with averaged results obtained from 50 random draws shown in the bottom right corner.

3D cine blinded reader in-vivo study

Dataset	Artifact reduction		Image sharpness	
	CS	CORe	CS	CORe
1	2.7	4.0	3.3	3.7
2	4.3	4.7	3.7	3.7
3	3.3	4.0	3.0	2.7
4	4.3	4.7	3.3	3.3
5	3.0	3.7	1.7	2.0
6	2.7	3.7	2.0	2.7
7	2.7	4.0	2.0	3.0
Average	**3.3**	**4.1**	**2.7**	**3.0**

Table 1 Results of a blinded reader study conducted on seven 3D cine datasets. Each score represents an average from three CMR expert readers on two criteria: artifact reduction and image sharpness. Score of 1 indicating non-diagnostic quality and a score of 5 representing a high-quality image.

Comparison of representative 3D cine frames

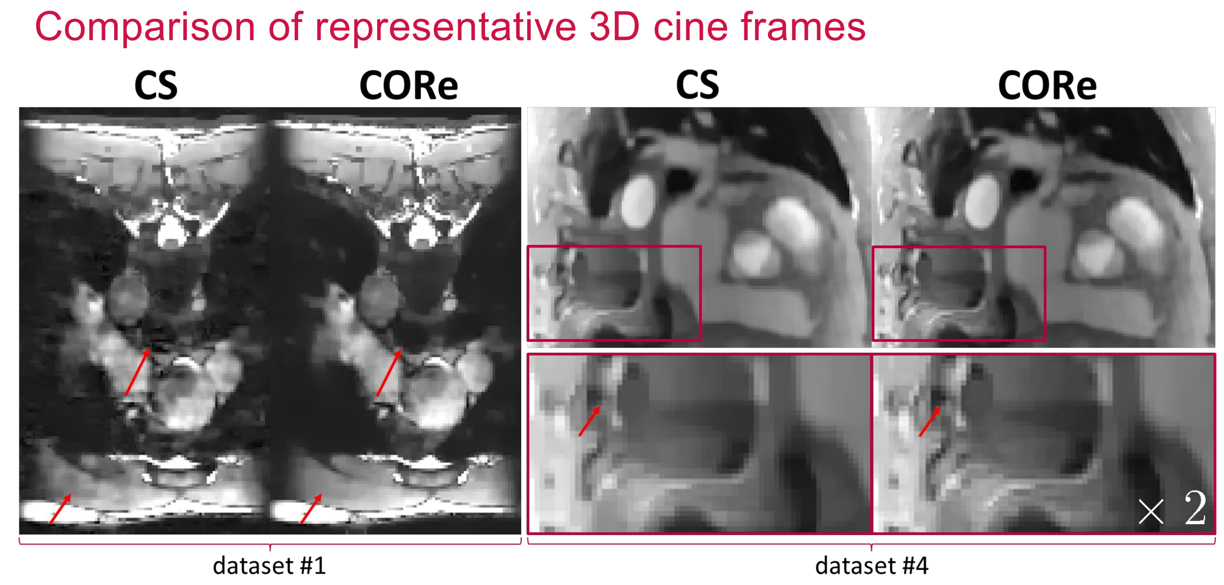

Figure 3 Comparison of two representative frames from 3D cine dataset #1 and #4 reconstructed using CS and CORe. The left example highlights the reduction of motion and flow artifacts in the axial view, as indicated by the (red) arrow. In the right example, CORe image appears to preserve more details.

4D flow quantification in-vivo study

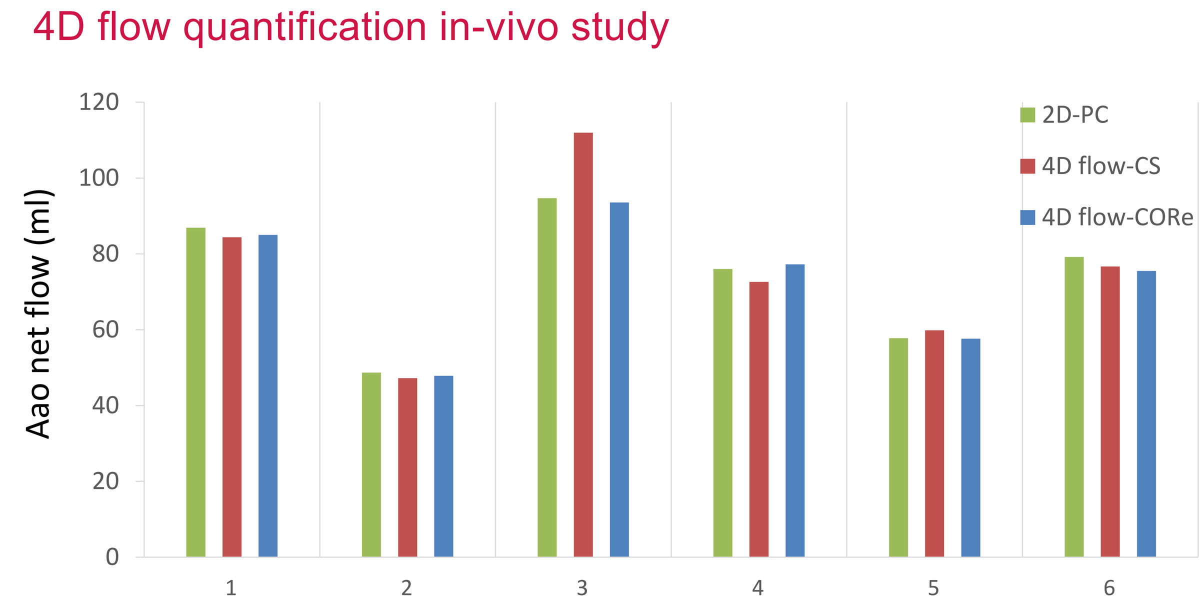

Figure 4 Comparison of Aao net flow measured from reconstructed 4D flow images using CS, CORe, and real-time 2D phase-contrast (2D-PC) at rest.

RESULTS

Phantom simulation study:

Figure 2 summarizes the results of the phantom study. The averaged results show that CORe outperforms CS, RR, and SO in terms of NMSE and SSIM of reconstructed images. Furthermore, Figure 2c highlights the advantage of using CORe, as SO is unable to eliminate entire outlier readouts.

3D cine in-vivo study:

The overall results of 3D cine reader study illustrated in Table 1, indicate that CORe is more effective than CS in reducing artifacts while preserving sharpness; this can be observed visually from the representative images shown in Figure 3.

Rest and stress 4D flow in-vivo study:

Net Aao flow values measured at rest using CORe and CS reconstructed 4D flow images are comparable with 2D-PC in most cases, as shown in Figure 4. For dataset#3, CS is showing significant overestimation, which can also be observed from the flow profile comparison demonstrated in Figure 5b. Figure 6 displays the bar plot comparing CS and CORe in stress 4D flow imaging for flow quantification across the five planes depicted in Figure 5a. The overall results demonstrate that CS shows significantly higher standard deviation of net flow values across Aao planes compared to CORe.

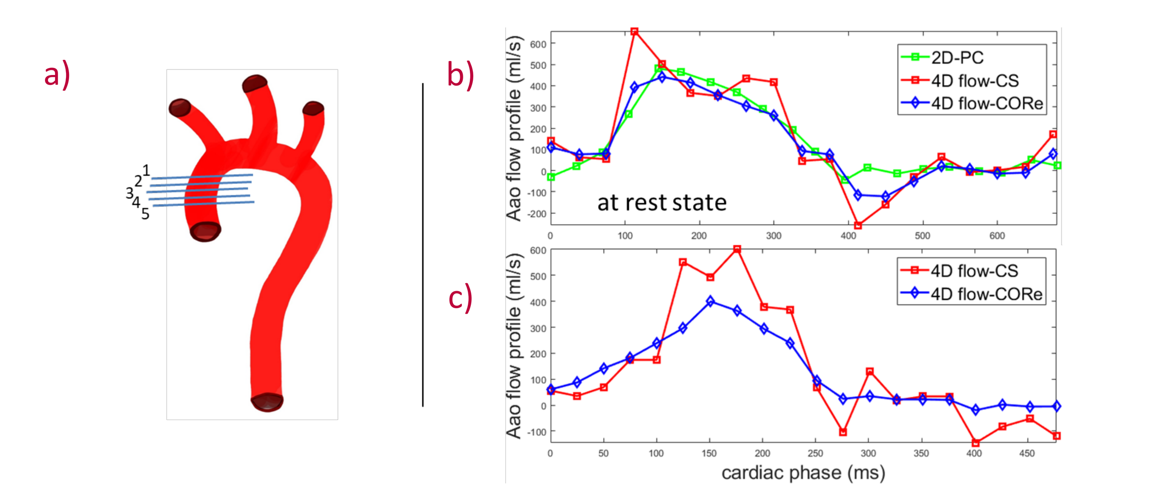

Figure 5 (a) Flow quantification planes defined at ascending aorta (Aao) for rest and exercise stress 4D flow analysis. (b) Volumetric flow rate profiles at Aao plane 1 from rest dataset#3 measured using 2D-PC, CS and CORe. (c) Volumetric flow rate profiles at Aao plane 1 from exercise dataset#3 measured using CS and CORe.

Stress 4D flow quantification

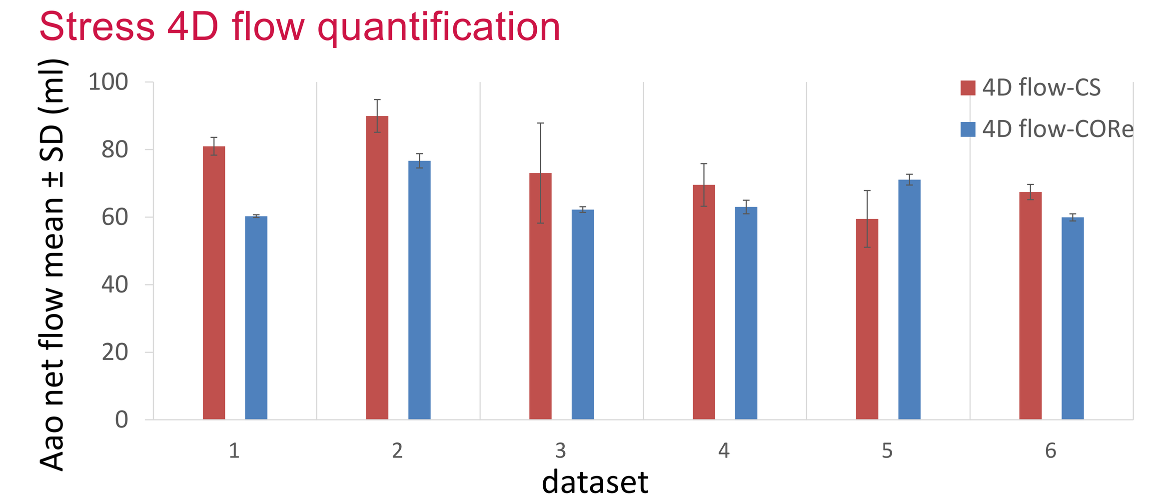

Figure 6 Comparison of Aao net flow mean ± SD measured from reconstructed exercise stress 4D flow images using CS and CORe.

Comparison of representative 4D flow frames

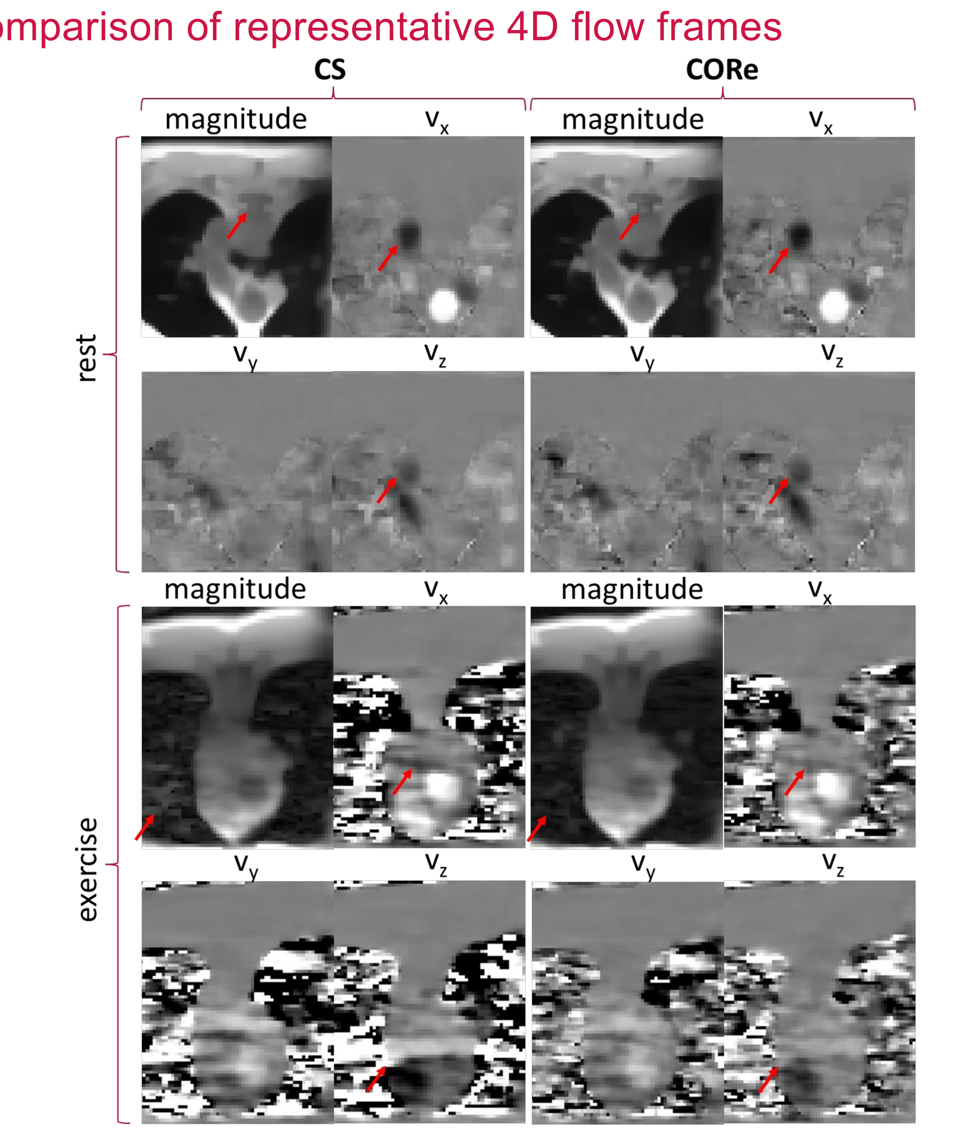

Figure 7 Visual comparison of representative magnitude and velocity components of 4D flow images at rest and exercise, reconstructed using CS and CORe. A single axial slice at systole (peak flow) is shown. The (red) arrow highlights the comparison of image sharpness in the rest dataset and artifacts in the exercise dataset.

CONCLUSION

In conclusion, the proposed method, CORe, integrates outlier rejection into the CMR reconstruction framework. Data from a 2D digital phantom, 3D cine and 4D flow rest and exercise stress imaging demonstrate that CORe is more effective in suppressing motion artifacts than traditional CS techniques.

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