

Motion artifact reduction in self-gated CMR 4D flow imaging under exercise stress

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SUMMARY:

Exercise stress 4D flow images are invariably corrupted with motion. Proposed Compressive recovery using Outlier Rejection (COrE) reduces motion artifacts. The method is validated using data from a digital phantom and exercise stress 4D flow imaging.

SYNOPSIS:

Free-breathing self-gated CMR 4D flow imaging using traditional Compressed Sensing (CS) methods invariably contains motion artifacts due to the inaccuracy of self-gating signal. Self-gating signal degrades even further in the case of exercise stress imaging due to excessive movement of the subject. We propose Compressive recovery with Outlier Rejection (COrE) to reduce the motion artifacts. We show proof-of-concept by comparing both CS and COrE for the reconstruction of a 2D bimodal dynamic phantom. Additionally, aortic flow quantification in exercise stress 4D flow imaging demonstrates stronger agreement between COrE and conventional 2D phase contrast, as compared to CS reconstruction.

INTRODUCTION:

In free-breathing Cardiac Magnetic Resonance (CMR) 4D flow imaging, the respiratory motion is compensated either by prospective navigator gating or by retrospective self-gating. Typically, these respiratory compensation methods do not suppress respiratory motion completely, leading to image artifacts. In the case of exercise stress imaging, the quality of the self-gating signal degrades even further due to irregular and exaggerated breathing patterns, and contamination from exercise-induced torso movement. In this work, we integrate an outlier rejection scheme into the image reconstruction process. This technique minimizes motion artifacts by suppressing contributions from k-space samples that have been erroneously assigned to the end-expiratory bin.

METHODS:

Typically used Compressed Sensing (CS) methods for accelerated 4D flow imaging employ an L2 norm for data fidelity and an L1 norm for regularization, i.e.,

$$\hat{\mathbf{x}} = \arg \min_{\mathbf{x}} \left\{ \frac{1}{2} \|\mathbf{A}\mathbf{x} - \mathbf{y}\|_2^2 + \lambda_1 \|\mathbf{W}\mathbf{x}\|_1 \right\}, \quad (\text{Eq. 1})$$

where $\hat{\mathbf{x}}$ is the recovered 4D MR image, \mathbf{x} represents the true image that we intend to reconstruct, \mathbf{y} is the collected k-space data which has been retrospectively sorted into a motion resolved respiratory bin by self-gating, \mathbf{A} is the sensing matrix, \mathbf{W} refers to undecimated wavelet transform and $\lambda_1 > 0$ is the regularization parameter.

Typically, 4D flow imaging data is collected continuously for several minutes. Then, the collected data are sorted into various respiratory bins using self-gating. Due to imperfections in the extracted self-gating signal, bin assignment for a small fraction of readouts is invariably incorrect. The quality of the images reconstructed with traditional CS (Eq. 1) can degrade substantially in presence of these outliers. We implement a motion robust extension of CS¹ which reduces the motion artifacts in the reconstructed image by suppressing the outliers in measured data. This model, termed Compressive recovery with Outlier Rejection (COrE), entails solving the following optimization problem:

$$\hat{\mathbf{x}} = \arg \min_{\mathbf{x}, \mathbf{v}} \left\{ \frac{1}{2} \|\mathbf{A}\mathbf{x} - (\mathbf{y} - \mathbf{v})\|_2^2 + \lambda_1 \|\mathbf{W}\mathbf{x}\|_1 + \lambda_2 \|\mathbf{v}\|_1 \right\}, \quad (\text{Eq. 2})$$

where \mathbf{v} represents the outliers in data and parameter $\lambda_2 > 0$ is a Lagrange multiplier. The term $\lambda_2 \|\mathbf{v}\|_1$ ensures sparsity of the outliers in the measurement domain. This model in Eq. 2 assumes that data

contains zero-mean Gaussian noise and sparse outliers, and reconstructs the image by (partially) eliminating the contribution of \mathbf{v} .

We compare both models, CS and CORE, for the reconstruction of a 2D image originating from a bimodal dynamic phantom. The dynamic phantom is simulated to transition between the expiratory and inspiratory phases (Figure 1). To simulate contamination with outliers, approximately 10% of the k-space data is randomly sampled from the inspiratory phase and the rest of the k-space is randomly filled with data from the expiratory phase. This contaminated k-space is used to reconstruct the expiratory phase image. The simulation is repeated 20 times, each with a random realization of the outlier locations in k-space. The acceleration rate was fixed at 3.5.

To validate the improvement offered by CORE in CMR 4D flow image reconstruction, twelve free-running, free-breathing, and fully self-gated 4D flow datasets were collected for a fixed acquisition time of 5 minutes using cartesian sampling². The datasets were acquired from 4 healthy volunteers (age range, 22-49 years) under different exercise stress conditions using a clinical 3T scanner (MAGNETOM Vida, Siemens Healthcare, Erlangen, Germany) and a cycle ergometer (MR Ergometer Pedal, Lode, The Netherlands). Three datasets were collected from each volunteer during rest state, exercise at 20 W and 40 W. To assess improvement in blood flow quantification using CORE as compared to CS (Eq. 1), real-time 2D phase-contrast MRI (2D-PC) was collected from all volunteers as a reference. Aortic net flow quantification over a cardiac cycle was performed using 2D-PC, CORE, and CS.

RESULTS:

In the dynamic phantom simulation, reconstruction of the expiratory phase using CS and CORE for 20 realizations yielded average PSNR values (in dB) of 24 ± 2.6 and 29.7 ± 1.8 , respectively. The improvement in recovered image quality is also evident in the example shown in Figure 1. Representative 4D flow magnitude and phase images from a single slice in axial view at systole are shown in Figure 2 for CS and CORE. The comparison demonstrates that the suggested model is more effective in suppressing motion artifacts, with the reduction in artifacts being more evident under exercise stress. Furthermore, net aortic flow values (Figure 3) measured from 4D flow images show that CORE, compared to CS, exhibits a stronger agreement with 2D-PC, with an average absolute difference of 7.4 ml for CORE and 13.4 ml for CS. Likewise, representative aortic flow rate profiles in Figure 4 show that CORE is more effective in suppressing motion artifacts.

DISCUSSION:

The parameters λ_1 and λ_2 used in CORE are chosen empirically. The values of λ_1 and λ_2 depend on the level of Gaussian noise; for a higher noise level, the values of λ_1 and λ_2 should be larger. The parameter λ_2 additionally depends on the percentage of outliers in data. A higher value of λ_2 will make \mathbf{v} sparser which implies less suppression of outliers, while a lower value of λ_2 will lead to less sparse \mathbf{v} , which means more suppression of outliers. The computation time for both CS and CORE reconstruction algorithms is comparable.

CONCLUSION:

The proposed method, CORE, integrates outlier rejection into the reconstruction framework. Data from a digital phantom and 4D flow exercise stress imaging demonstrates that CORE is more effective in suppressing motion artifacts than traditional CS techniques.

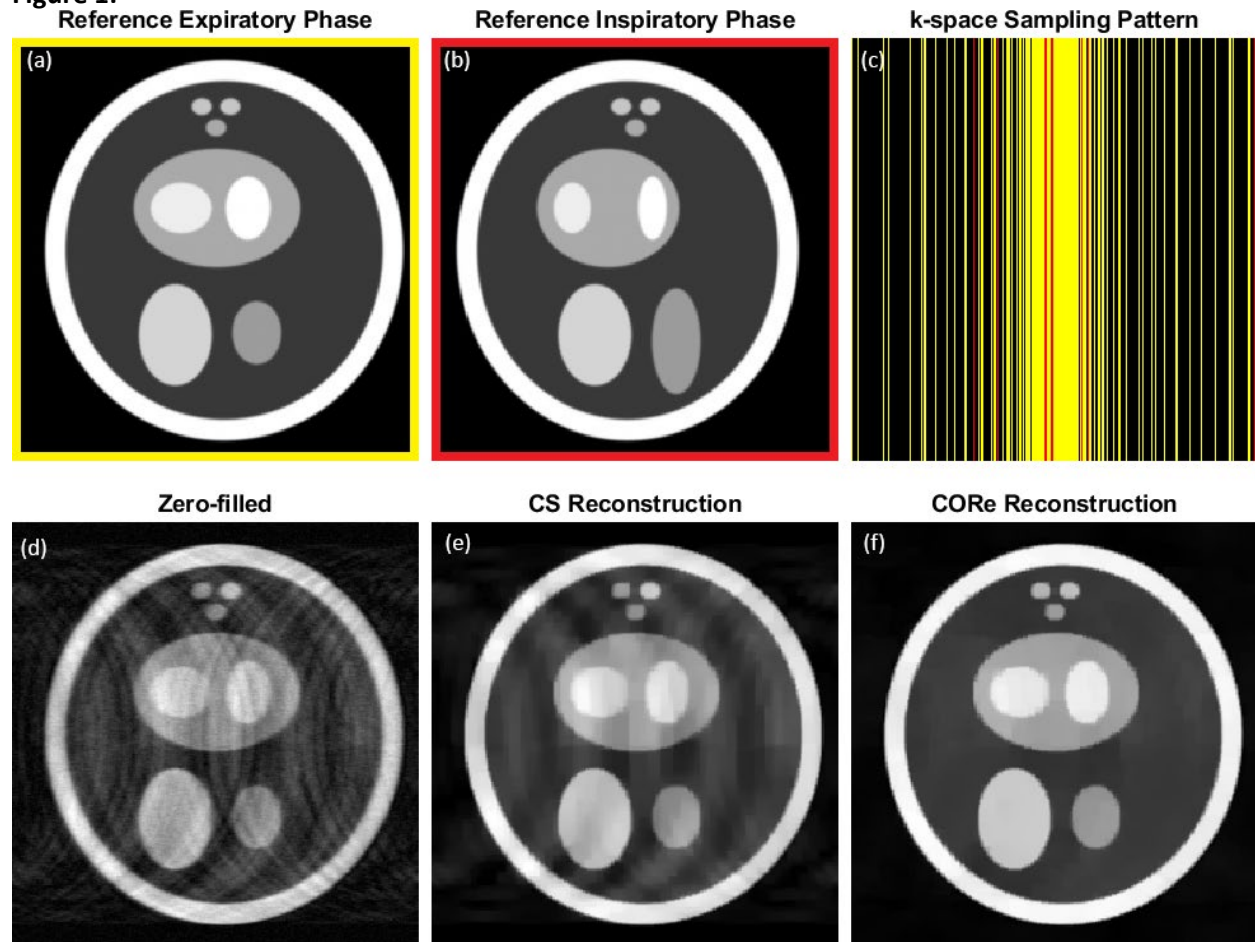
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- [1] Bin Dong, H. J. (2012). Wavelet frame based blind image inpainting. *Applied and Computational Harmonic Analysis*, 268-279.
- [2] Pruitt, A. R. (2020). Fully self-gated whole-heart 4D flow imaging from a 5-minute scan. *Magn Reson Med.*, 1222– 1236.

Acknowledgments:

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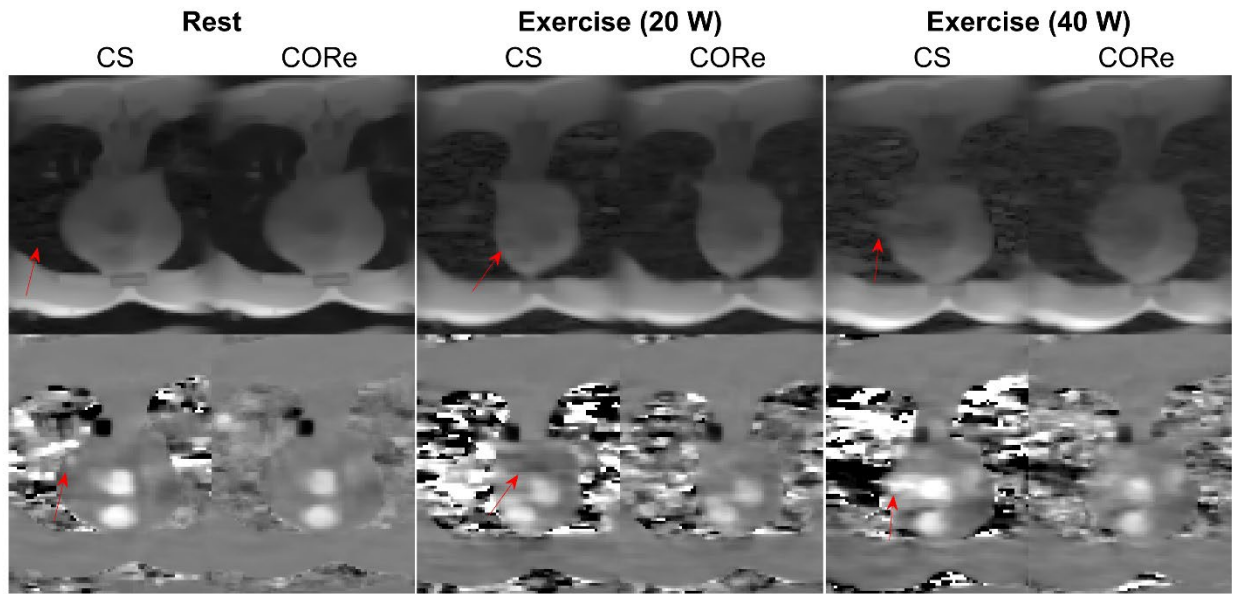
Figure 1:



Caption:

A realization from the dynamic phantom study. (a) Fully sampled reference frame from the expiratory phase of the bimodal dynamic phantom, (b) Fully sampled reference frame from the inspiratory phase of the phantom, (c) k-space sampling pattern, black represents encodings not sampled, yellow and red represent encodings sampled from expiratory and inspiratory phases, respectively, (d) zero-filled image obtained by the inverse Fourier transform of the contaminated k-space, (e) expiratory phase image recovered using CS, and (f) expiratory phase image recovered using CORE.

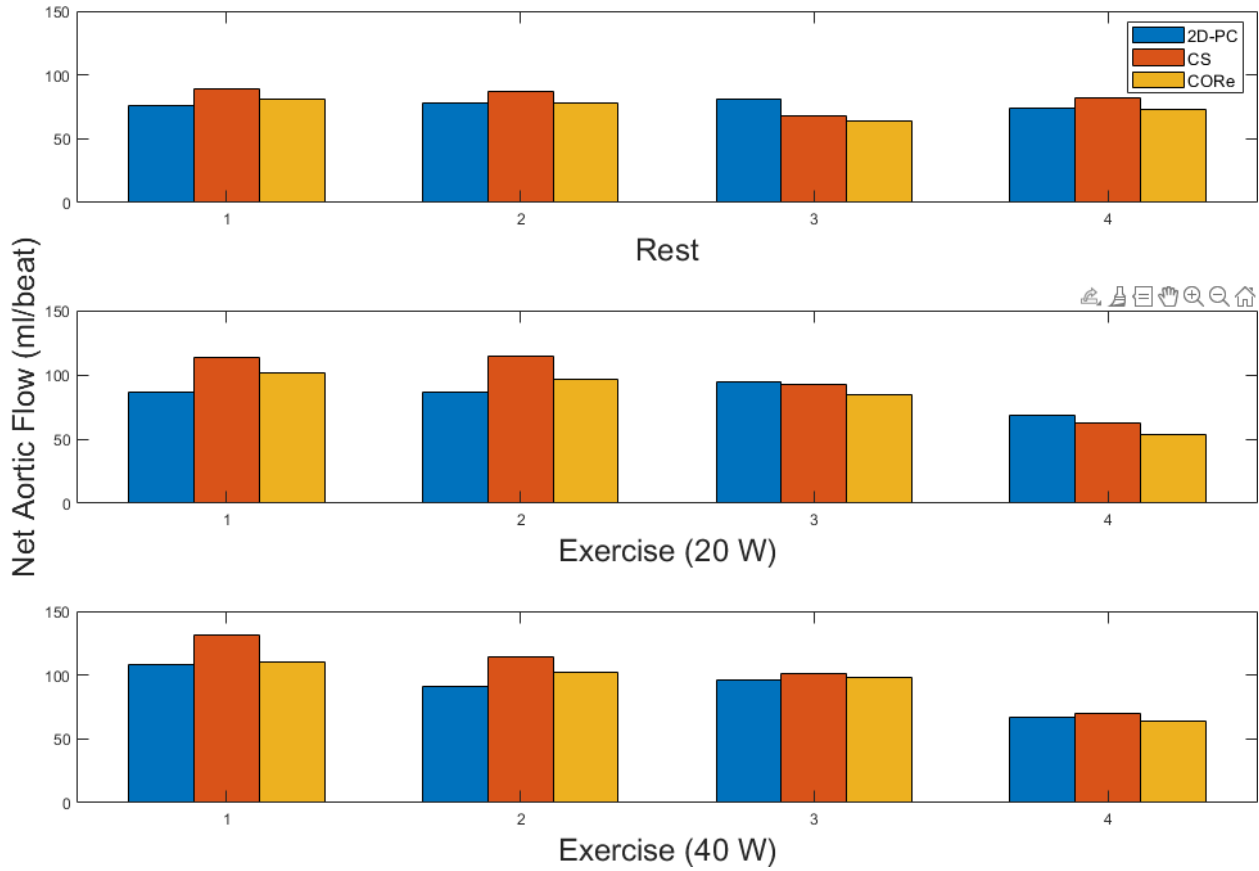
Figure 2:



Caption:

Visual comparison of magnitude and a velocity component of 4D flow images reconstructed using CS and COfRe. A single axial slice is shown at systole (peak flow). The red arrows highlight some of the visible artifacts in CS images that have been suppressed by COfRe.

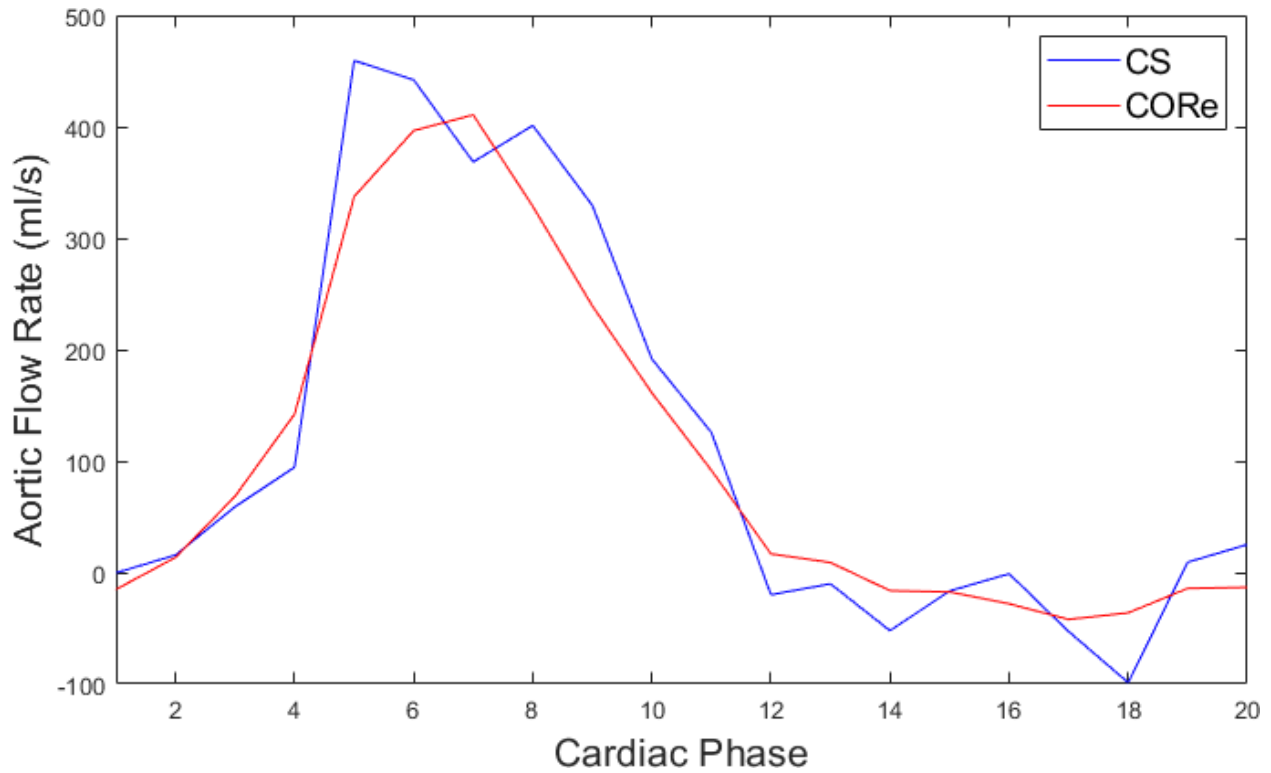
Figure 3:



Caption:

Comparison of net aortic flow measured from reconstructed 4D flow images using CS, CORE, and real-time 2D phase-contrast (2D-PC). The comparison is based on flow measurements from four subjects under three different stress conditions: rest, exercise at 20 W, and exercise at 40W.

Figure 4:



Caption:

Comparison of CS and CORe representative aortic flow rate profiles under exercise stress (20 W) measured from the reconstructed 4D flow images. The motion-induced oscillations are visible in CS but not in CORe.