Real-Time Phase Contrast Cardiovascular Flow Imaging with Joint Low-Rank and Sparsity Constraints

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Introduction: Phase contrast (PC) cardiovascular flow imaging has been developed into a powerful tool for quantification and visualization of blood flow dynamics in the heart and great vessels. Most PC flow MRI techniques employ ECG synchronized cine acquisitions with proper respiration control to acquire data from multiple cardiac cycles [1, 2], from which spatiotemporally averaged velocity maps are reconstructed. The underlying assumptions of the cine-based imaging limit its applications to cardiac experiments with significant irregularities (e.g., cardiac arrhythmias). Real-time PC cardiovascular flow MRI, as a promising direction to address these limitations, has become a recent research focus [3, 4]. For real-time PC flow imaging, (k, t)-space is often highly undersampled, resulting in a significantly more challenging reconstruction problem than that in cine-acquisitions. Although a number of model-based reconstruction methods (e.g., [5-7]) have been proposed for cine-based flow imaging, few of them have been demonstrated for real-time flow imaging applications. In this work, we present a novel method for real-time PC flow imaging, which effectively integrates a real-time acquisition scheme (without ECG gating and respiration control) with a new constrained reconstruction method using joint low-rank and sparsity constraints. We illustrate the performance of the proposed method in an in-vivo real-time PC flow imaging experiment with velocity encoding in multiple directions.

Proposed Method: For simplicity of notation, the proposed method is described for the case with one velocity encoding direction (extension to velocity encoding in multiple directions is straightforward). Let $\mathbf{I}_1$ and $\mathbf{I}_2$ denote the spatiotemporal Casorati matrices for reference and velocity encoded image sequences, respectively. Due to the strong spatiotemporal correlation in each of these cardiac image sequences, the partial separability model [8], or equivalently the low-rank model, can be used to represent $\mathbf{I}_1$ and $\mathbf{I}_2$, i.e., $\mathbf{I}_1 = \mathbf{U}_1\mathbf{V}_1$ and $\mathbf{I}_2 = \mathbf{U}_2\mathbf{V}_2$, where $\mathbf{U}_1$ and $\mathbf{U}_2$ respectively span the spatial subspaces of $\mathbf{I}_1$ and $\mathbf{I}_2$, and $\mathbf{V}_1$ and $\mathbf{V}_2$ respectively span the temporal subspaces of $\mathbf{I}_1$ and $\mathbf{I}_2$. Furthermore, even stronger low-rank constraints can be enforced by pre-determining the temporal subspaces $\mathbf{V}_1$ and $\mathbf{V}_2$ from the navigator data using principal component analysis [8]. As a consequence, image reconstruction problem reduces to determination of the spatial subspaces $\mathbf{U}_1$ and $\mathbf{U}_2$. In addition to low-rank constraints, $\mathbf{I}_1$ and $\mathbf{I}_2$ also have sparse representations in certain transform domains. Specifically, two sparsity constraints are considered: 1) spatial-spectral sparsity of each cardiac image sequence, and 2) sparsity of the complex difference (i.e., angiogram) between $\mathbf{I}_1$ and $\mathbf{I}_2$. Integrating the above low-rank and sparsity constraints, the reconstruction problem can be formulated as follows:

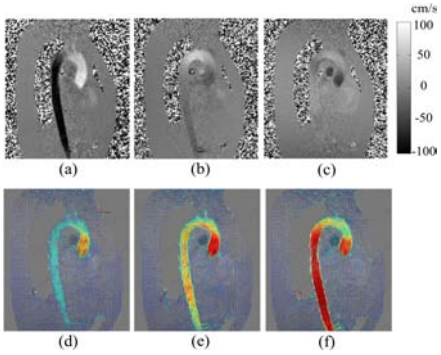

Fig. 1 Reconstructions and visualizations: (a)-(c) reconstructed velocity maps in FH, AP, and RL directions at one time frame; (d)-(f) pathline visualization of three time frames, during which blood flows through the aorta.

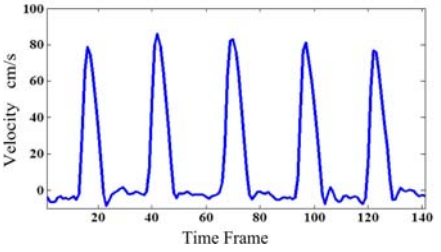

Fig. 2 Reconstructed flow profiles for a ROI in the ascending aorta over five cardiac cycles.

$$\{\hat{\mathbf{U}}_1, \hat{\mathbf{U}}_2\} = \arg\min \underbrace{\sum_{i=1}^{2} \left\| \mathbf{d}_i - \mathbf{E}_i\mathbf{U}_i\mathbf{V}_i \right\|_2^2}_{\text{low-rank constraints}} + \underbrace{\lambda_1 \left\| \mathbf{U}_1\mathbf{V}_1 - \mathbf{U}_2\mathbf{V}_2 \right\|_1}_{\text{sparsity of angiogram}} + \underbrace{\lambda_2 \sum_{i=1}^{2} \left\| \mathbf{U}_i\mathbf{V}_i\mathbf{F}_t \right\|_1}_{\text{spatial-spectral sparsity}}, \quad (1)$$

where $\mathbf{d}_1$ and $\mathbf{d}_2$ respectively denote the acquired imaging data for reference or velocity-encoded sequences, $\mathbf{E}_1$ and $\mathbf{E}_2$ respectively denote the imaging operator incorporating parallel imaging and (k, t)-space sparse sampling for the reference and velocity-encoded sequences, $\mathbf{F}_t$ denotes the temporal Fourier transform matrix, λ_1 and λ_2 are the regularization parameters. The resulting problem in (1) is a convex optimization problem, which can efficiently solved by half-quadratic regularization with a continuation procedure [9]. After the image reconstruction, the phase difference or velocity map can be determined.

Results: We evaluated the proposed method in a 2D real-time PC flow imaging experiment with three directional velocity encodings. The experiment was performed on a Philips Medical Systems 3.0T scanner with 32-channel cardiovascular coils. No ECG gating and respiration control were used in the experiment. The imaging parameters were: FOV = 352 mm × 259 mm, spatial resolution = 2.59 mm × 2.59 mm, matrix size = 136 × 100, temporal resolution = 34.4 ms, slice thickness = 5 mm, flip angle = 5°, TR/TE = 4.3/2.7 ms, k-space segments = 4, VENC = 200 cm/s for the feet-head (FH) direction, 150 cm/s for the anterior-posterior (AP) direction, and 150 cm/s for the right-left (RL) direction, acceleration factor = 33, and total acquisition time = 136 s. Fig. 2 (a)-(c) show the reconstructed three-directional velocity maps for one time frame. Fig. 2(d)-(e) show the pathline visualization of the velocity maps at three time frames during which the blood flow through the aorta. It illustrates that the proposed method can achieve high-quality reconstructions from highly undersampled data for real-time imaging. Fig. 2 shows the temporal flow profile of one ROI in the ascending over five cardiac cycles. As can be seen, the beat-by-beat variability of blood flow was clearly resolved from the reconstructed flow profile, demonstrating the unique advantages of real-time imaging over the cine-based imaging.

Conclusion: We presented a new method for real-time PC flow imaging, which reconstructs three directional velocity maps with high spatiotemporal resolution. It also can resolve beat-by-beat variation of blood flow dynamics. We demonstrated the performance of the proposed method in a 2D real-time PC flow MRI experiment.

References: [1] M. Markl et al. JCMR, 13:7, 2011. [2] M. Markl et al. JMRI, 26:1015-1036, 2012. [3] A. Joseph et al. NMR Biomed, 25:917-924, 2012. [4] A. Joseph et al. JMRI, 2013. [5] C. Baltes et al. MRM, 54:1430-1438, 2005. [6] D. Kim et al. MRM, 67:1054-1064, 2012. [7] D. Giese et al. MRM, 69:434-443, 2013. [8] Z.-P. Liang, IEEE-ISBI, 988-991, 2007. [9] B. Zhao et al. IEEE TMI, 1809-1820, 2012.