

A Bayesian Approach for Accelerated Phase Contrast MRI

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Purpose: Phase-contrast magnetic resonance imaging (PC-MRI) can noninvasively characterize hemodynamics in the heart and great vessels, providing quantification of cardiac function, evaluation of valvular stenosis, and assessment of congenital heart disease. Compared to 1D measurements with gold standard Doppler ultrasound, PC-MRI is able to perform volumetric measurements while simultaneously encoding three velocity directions on a per-voxel basis (4D flow); thus, PC-MRI can provide accurate and robust flow quantification. Despite recent improvements, acquisition time for 4D flow imaging remains long, ranging from 15-30 minutes for a volume covering the heart¹ and therefore limiting clinical application. Here, we aim to reduce acquisition time of PC-MRI using Bayesian inference.

Theory: A novel Bayesian inference technique is proposed for accelerated PC-MRI that exploits the physical relationships between data samples across space, time, coils, and velocity encodings. Four characteristics distinguish the approach from prior art. First, we employ non-decimated wavelets for transform-based compression jointly across space and time. Second, generalized approximate message passing² provides a fast computational framework to enable minimum mean squared error estimation while jointly processing the large corpus of PC-MRI data. Third, an optimized sampling strategy³ provides different variable density sampling patterns for each frame and each encoding. Fourth, the strong redundancy between the velocity-compensated and velocity-encoded images is captured using a mixture density; the approach captures not only the similarity in magnitudes between velocity-compensated and velocity-encoded images, but also the phase similarity in zero-velocity regions. The two components of the mixture pdf are shown in Fig. 1, with color denoting probability on [0,1]. The algorithm implicitly learns a probabilistic segmentation of image frames into regions of zero versus non-zero flow. Together, these four characteristics yield a principled estimation approach that enables accelerated PC-MRI.

Methods: Fully sampled data with two spatial dimensions and one velocity encoded direction were collected from a healthy volunteer on a 1.5T Avanto (Siemens) scanner with an 18 coil cardiac array within a single breath-hold using a phase-contrast, segmented, gradient-echo sequence and ECG gating. The data were retrospectively undersampled and processed at eight different acceleration rates (R=2, 4, 6, 8, 10, 12, 14, 16) using VISTA sampling³. In addition, prospectively undersampled data were collected with uniform R=2 with ACS lines and VISTA R=8 sampling patterns from a separate, healthy volunteer. Peak velocity and stroke volume were used as performance metrics. Coil sensitivity maps are estimated from time-averaged data. Maxwell phase corrections were applied to the data during reconstruction as part of the Bayesian model.

Results and Discussion: As evident from Fig. 2 for retrospective undersampling, peak velocity and stroke volume estimates are maintained to R=12, which corresponds to 3.75 s acquisition time. Using un-optimized custom Matlab (Mathworks) code message passing on a factor graph representing the proposed data model, provides reconstruction in 3 minutes for the data volume of 166x108 images with 20 frames per encoding. The image segmentation implicit in the mixture density model is shown in Fig. 4(c). Mean and peak flow profiles from the prospectively undersampled data are given in Fig. 3, showing agreement of R=8 results with GRAPPA reconstruction at R = 1.74.

Conclusion: A new approach has been presented for accelerated PC-MRI that exploits not only spatio-temporal compressibility but also physical correlations across velocity encodings. The proposed method provides a path to clinical demonstration of 4D flow imaging within a *single breath hold*, providing improved flow quantification, lower cost, and increased patient comfort.

References: [1] Markl et al., JCMR 2011; 13:1. [2] Rangan, IEEE ISIT 2011; p2168. [3] Ahmad et al., MRM 2014; doi 10.1002/mrm.25507.

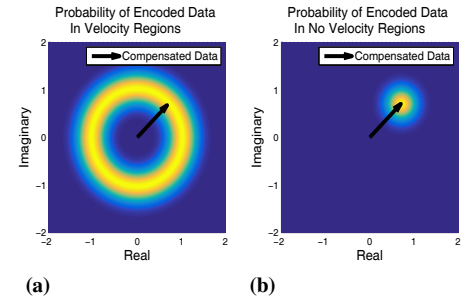


Figure 1: Conditional distribution of velocity encoded data given compensated data. (a) In velocity regions, magnitude is constrained and phase is unconstrained. (b) In regions without velocity, phase is also constrained.

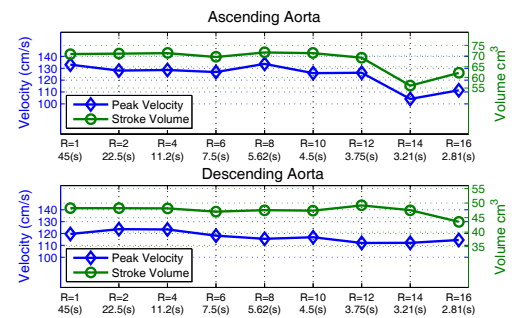


Figure 2: Peak velocity and stroke volume for the ascending and descending aorta versus acquisition time.

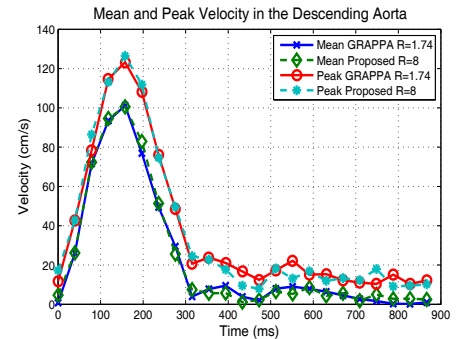


Figure 3: Peak and mean velocity versus time using prospectively undersampled data for GRAPPA R=1.74 and the proposed method R=8.

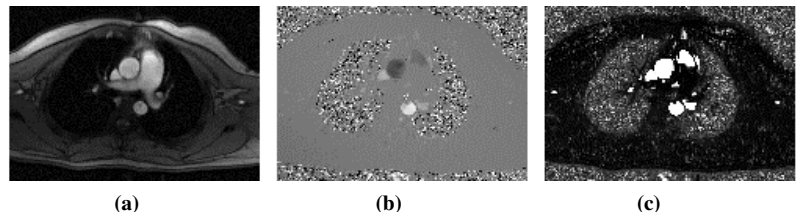


Figure 4: Example reconstruction given in Fig. 3 using the proposed method at R=8. (a) The magnitude image. (b) The velocity (phase) map. (c) Probability of flow present in a voxel produced by the proposed approach in grayscale from 0 (black) to 1 (white).