High dynamic range magnetic resonance flow imaging in the abdomen

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EE 367 Project Proposal

1 Motivation

Time-resolved, volumetric phase-contrast magnetic resonance imaging (also known as 4D flow MRI) is a powerful clinical tool used by radiologists to simultaneously assess cardiovascular anatomy, flow, and function [1]. With raw data acquired in one 8-10 minute scan, both anatomical and flow images can be reconstructed by encoding tissue velocity information into the phase of the raw MRI signal.

The velocimetric dynamic range of 4D flow MRI is inherently limited, however. Since signal is measured in quadrature (via real and imaginary channels), the principal value of the complex MRI signal can only take on values in the range $(-\pi, +\pi]$. Thus, there is a maximum encodable velocity also known as *venc*. This is a prescribable parameter which determines the range of velocities $(-venc, +venc]$ which are directly measurable from a single scan. To avoid velocity aliasing (also known as phase wrapping), the *venc* is set higher than the highest velocity that the MRI technician expects to measure. However, scanning with higher *venc*'s comes at the cost of velocity-to-noise ratio (VNR). This becomes detrimental in abdominal flow imaging due to the presence of a high dynamic range of flow velocities in the abdomen. The *venc* must be set high to capture fast flow dynamics, making VNR too low to resolve slow flow dynamics (See Figure 1).

In this work, I will propose a scheme where multiple 4D flow datasets are acquired with different *venc*'s, and then fused together using a regularized high dynamic range post-processing technique to precisely and accurately depict both fast and slow flow. This technique would not only help streamline visualization of this high-dimensional data, but also increase precision and accuracy of biomarkers which are derived from flow data such as peak velocity, flow, wall shear stress, and turbulent kinetic energy.

2 Related Work

The velocimetric dynamic range of 4D flow MRI has previously been extended in three ways: a) high VNR velocity encoding [2] b) phase unwrapping techniques [3,4], and c) multi-venc flow imaging [5,6]. The performance of the first technique is highly dependent on spatial and temporal resolution especially in fatty areas such as the abdomen. For this proposal, I will focus on the second and third techniques.

Phase unwrapping is a well-studied image processing technique that has recently been applied to 4D flow in order to undo velocity aliasing in low *venc* acquisitions (See Figure 2). By estimating four-dimensional (space and time) gradients in the raw phase data, algorithms find and undo

phase wraps by locating areas with local "jumps" of 2π. This can be done non-iteratively by analytically solving Poisson's equation [3], or iteratively by weighted least squares [4]. In general, phase unwrapping has been shown to be non-robust in 4D flow data, and its performance is highly dependent on patient anatomy and physiology.

Multi-venc 4D flow MRI is another technique that extends dynamic range by acquiring multiple datasets using different *venc*'s and then using high *venc* datasets to unwrap phase in low *venc* datasets. Algorithms look at element-wise differences between low and high *venc* data, and locate phase wraps by thresholding voxels with differences above 2π [5]. However, acquiring multiple 4D flow datasets is costly, so most techniques propose only acquiring two datasets with one high and one low *venc* [6]. In the end, most of the high *venc* data is thrown away since low *venc* data is replaced with high *venc* data only where wraps occur. While this technique has shown to be highly robust to velocity aliasing, its use of data is inefficient.

3 Project Overview

For my project, I will apply the high dynamic range processing technique [7] to reconstruct multi-venc 4D flow datasets using as much of the raw data as possible. Given magnitude images $M_i \in \mathrm{R}^m$ and velocity images $V_i \in \mathrm{R}^m$ acquired with venc_i for $i \in \{1, ..., n\}$, estimate composite HDR velocity image $\hat{V}$ by the following least absolute shrinkage and selection operator (LASSO) minimization:

$$\text{minimize} \sum_{i=1}^{n} ||W_i^\intercal (V_i - \hat{V})||_2^2 + \lambda ||\Psi(\hat{V})||_1$$

$$W_{ij} = w_{\mathrm{VNR}}(M_{ij}) w_{\mathrm{wrap}}(\mathrm{venc}_i)$$

This minimization problem can be solved using a simple weighted average for $\lambda = 0$, or the alternating direction method of multipliers (ADMM) for $\lambda > 0$. The design of the cost function can be decomposed into two problems:

- **Designing the weights:** Assuming that the highest *venc* dataset has no velocity aliasing (as are datasets acquired in the clinic), we can roughly estimate which voxels in the low venc datasets are wrapped and weigh against them. We can also weigh against measurements with low VNR, a parameter that can be estimated from corresponding magnitude data.
- **Incorporating a priori information:** An l_1-regularization term is introduced to incorporate prior information into the reconstruction of composite HDR images. This could be a total variation penalty to enforce flow smoothness, although this may not necessarily be true in the presence of flow jets caused by narrow vessels. It could also be a divergence penalty, which has previously been used to denoise 4D flow data [8]. This idea derives from a classical fluid dynamics result that flow fields have zero divergence (incompressibility).

Below I have outlined two experiments I will perform for this project, as well as one optional experiment that I may or may not complete depending on time:

1. **HDR phantom simulations:** From a previous project, I have Matlab code that can simulate 4D flow data acquired with different *venc*'s (See Figure 3). The HDR method with different priors and values of λ will be applied and evaluated by computing RMSE and PVNR (peak velocity-to-noise ratio) between HDR images and ground truth images. I will also investigate how many different *venc* images are required to get good results.

2. **HDR in-vivo:** The HDR method will also be applied to in-vivo multi-venc abdominal data, which has yet to be acquired. Through access to the MRI scanners at Stanford Lucas Center, I will be able to scan a volunteer from my lab. In this experiment, I will not have a ground truth, since fully-sampled 4D flow datasets take hours to acquire, and no volunteer (or patient) will want to sit in the scanner for hours. Therefore, the evaluation will be mostly qualitative.

3. **HDR + super-resolution (optional):** In order to address the long scan time required to acquire a multi-venc dataset, one could undersample each *venc* dataset, or a subset of the datasets. Then, the HDR objective function would require the modification:

$$\text{minimize} \sum_{i=1}^{n} ||W_i^\intercal (AV_i - \hat{V})||_2^2 + \lambda ||\Psi(\hat{V})||_1$$

where A is an interpolation or super-resolution matrix, which artificially increases the spatial and/or temporal resolution of the inputs V_i.

4 Timeline

1. Week 1 (2/13 - 2/19): Develop HDR code (weighted average and ADMM implementation) in Matlab
2. Week 2 (2/20 - 2/26): Phantom simulations, acquire in-vivo data
3. Week 3 (2/27 - 3/5): Apply HDR to in-vivo data
4. Week 4 (3/6 - 3/12): Begin making poster, attempt super-resolution problem
5. Week 5 (3/13 - 3/17): Present poster, write final report

5 Figures

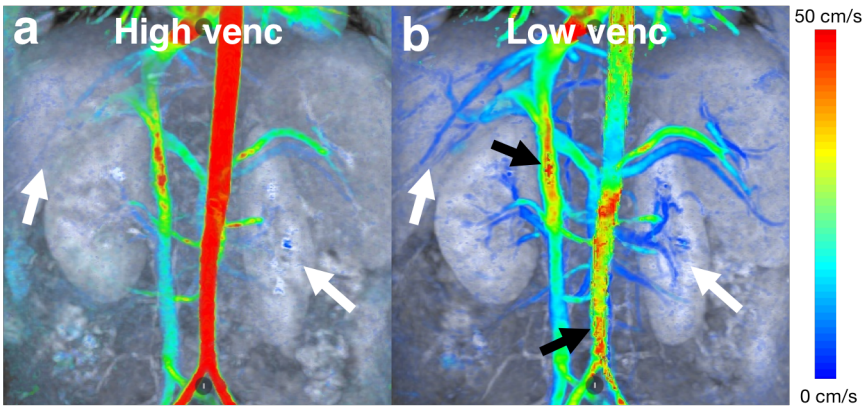

Figure 1: High *venc* vs. low *venc*. Two abdominal 4D flow datasets obtained with *venc*'s of (a) 120 cm/s and (b) 50 cm/s. Color velocity data is scaled from 0 to 50 cm/s and overlaid on top of grayscale magnitude data. As shown here, low-*venc* data is prone to velocity aliasing in high velocity structures (black arrows), but offer much better low velocity resolution as seen by the renal and hepatic vasculature (white arrows). The idea behind this project is to use HDR techniques to combine two (or more) datasets like these into one composite dataset with good low velocity resolution and without velocity aliasing.

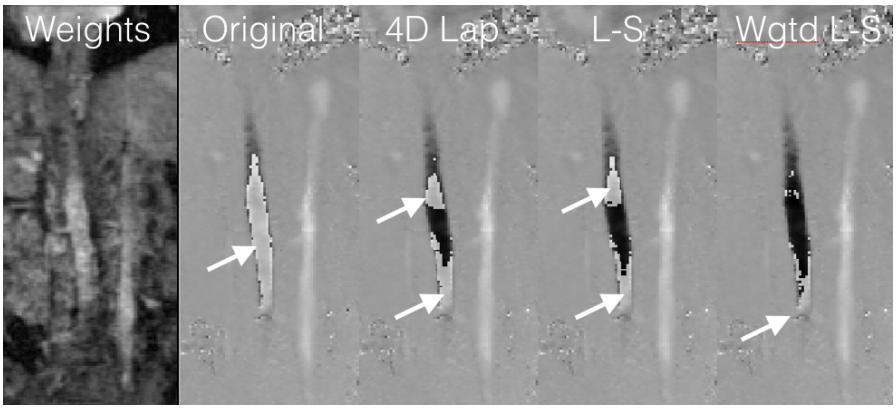

Figure 2: Performance of three phase unwrapping algorithms on low-*venc* abdominal data. 4D raw phase data is projected down onto a 2D coronal slice of the abdominal aorta. Phase wraps in each image are denoted by white arrows.

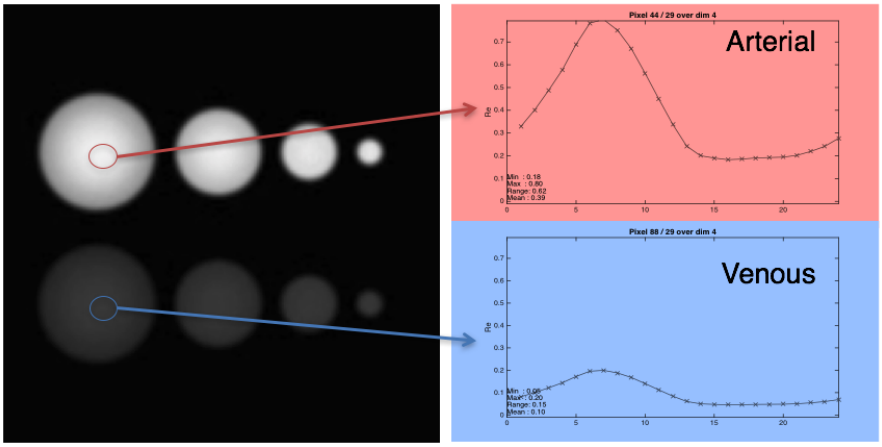

Figure 3: Simulated flow data. 4D flow data (magnitude and phase) of ideal cylindrical vessels can be simulated using a common computational fluid dynamics algorithm known as the Womersley method. This data can be simulated for arbitrary spatial resolution, temporal resolution, *venc*, and peak velocity. Velocity profiles for both arterial (red) and venous (blue) vessels are shown here.

6 References

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