Improved Visualization and Quantification of 4D Flow MRI Data using Divergence-free Wavelet Denoising

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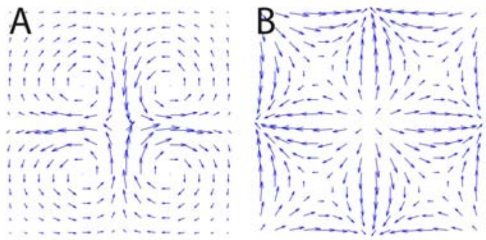

Figure 1 *2D slice of DFW basis functions: div-free (A), non-div-free (B)*

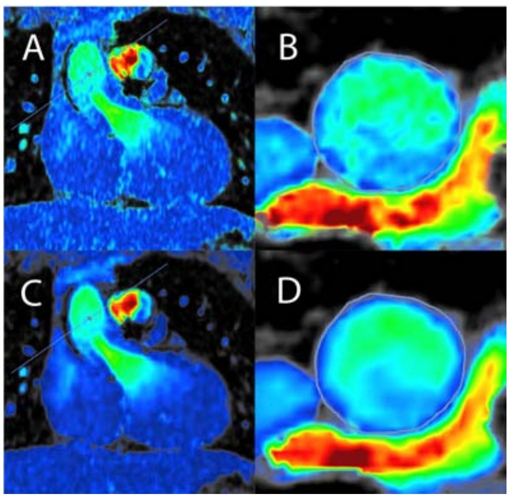

Figure 2 (in color) *Visualization of cardiac flow magnitudes before denoising (A) with closeup of segmented aorta slice (B), and after denoising (C) with closeup of segmented aorta slice (D).*

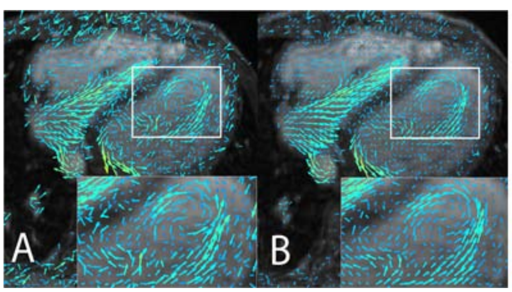

Figure 3 (in color) *Vector visualization of axial cross-section of cardiac flow: acquired data (A), denoised data (B)*

Purpose: 4D flow MRI has the potential to provide global quantification of cardiac flow [1], yet often suffers from low velocity-to-noise ratio. Since blood flow is incompressible, it is approximately divergence-free (div-free). Therefore, most of the divergence components in the flow field originate from noise, which can be reduced by enforcing the reconstructed flow to be div-free. Several methods were proposed to reconstruct div-free flow field from noisy flow data and were shown to be effective as a denoising process [2,3,4]. In practice, however, discrete approximation of flow near edges cannot be fully captured by strict div-free representation. Enforcing such a solution may lead to error propagation throughout the flow field. Here, we aim to provide a practical div-free enforcing processing using divergence-free wavelet (DFW) that has the following properties: 1) enforce "soft" div-free constraints where appropriate 2) multiscale representation 3) adaptive to noise 4) computationally fast. In addition, we utilize sparsity of flow data in DFW domain [5] for further denoising by performing wavelet shrinkage [6].

Theory: DFW is constructed by tensor combinations of a pair of 1D wavelets that are related by differentiation following the instructions in [5]. One example is the pair of linear and quadratic spline wavelets, which results in DFW functions shown in Figure 1. Since DFW separates flow data into div-free and non-div-free components in wavelet domain, we propose soft-thresholding DFW coefficients to encourage sparsity; in addition, we soft-threshold non-DFW coefficients with a higher threshold to softly enforce div-free constraints instead of eliminating all divergence. Soft-thresholding non-div-free coefficients allows the flexibility to adjust the cutoff so that important non-div-free components, such as those arising near edges, persist. Because of the simplicity of the tensor combinations of 1D wavelet functions, the procedure of DFW denoising maintains O(N) complexity.

Methods: To validate the improvement, in-vivo 4D cardiac flow data were acquired in 8 patients (20 heart phases, 122-44 slices, mean resolution=1.56x1.56x1.43mm^3) on a GE 1.5T Signa Scanner. Flow data were extracted from eddy-current corrected phase of reconstructed images using L1-SPIRiT [7]. Segmentations were done manually on aorta and pulmonary trunk. Net flow rate (volume/time) and regurgitant fraction (RF, %) were then calculated for each segmentation. Flow inconsistency was defined as the absolute difference between flow rates in the aorta and pulmonary trunk and should generally equal to zero for noiseless data.

Results and Discussion: Both Figure 2 and 3 show significantly improved visualization after post-processing. Studies were evenly separated into a group with RF less than 5% (mean net flow=2.945 L/min) and a group with RF more than 30% (mean net flow=2.212 L/min). For the first group, the average flow inconsistency before denoising was 0.395 L/min and after denoising was 0.353 L/min, yielding a 10.7% improvement. Average change in RF was 0.08%. For the second group, the average flow inconsistency before denoising was 1.151 L/min and after denoising was 0.926 L/min, yielding a 19.5% improvement. Average change in RF was 1.88%. Each processing of a 3D volume ran within half a minute in Matlab on a 2.8GHz Core2Duo laptop with 4GB of RAM.

Conclusion

DFW denoising was shown to enhance the visual quality of flow data while improving quantification of flow at aorta and pulmonary trunk. The improved flow consistency and small change in RF suggests that DFW denoising can be safely applied on clinical data without distorting quantifications.

References

[1] Markl, et al. JMRI, 2003;17(4);499-506, [2] Busch, et al. MRM 2012, [3] Song, et al. JMRI, 1993;4(7);587-596, [4] Leocher, et al. ISMRM 2012;1246, [5] Deriaz, et al. J. Turbul 2006;1, [6] Donoho, et al. Biometrika, 1994;3(4): 425-55, [7] Lustig et al. MRM 2010;64(2):457-471