Sparse representations for compressed sensing acceleration of Fourier velocity encoded MRI

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Introduction Fourier velocity encoded (FVE) MRI [1] is useful in the assessment of vascular and valvular stenosis [2] and intravascular wall shear stress [3,4], as it eliminates partial volume effects that may cause loss of diagnostic information in more conventional phase-contrast MRI [5]. FVE MRI has not been adopted for any routine clinical applications, primarily because scan-time is prohibitively long. However, FVE shows great potential for compressed sensing (CS) acceleration [6], due to its high dimensionality and intrinsic sparseness in image domain. Gamper et al. successfully applied CS to FVE imaging, using a Fourier transfom along the temporal dimension as sparsifying transform [7]. In this work, we investigate other sparse representantions for FVE data, using a five-dimensional (x,y,z,v,t) FVE dataset of the neck (focusing on carotid flow). Several combinations of separable transforms were evaluated. Two promising combinations of transforms are proposed.

Data acquisition Multi-slice CINE spiral FVE scans were performed on a GE Signa 3T EXCITE HD system (40 mT/m, 150 T/m/s gradients), using a 4-channel carotid coil. Scan parameters:1.4×1.4×5 mm^3 spatial resolution (8×1012-sample variable-density spiral readouts), 5 cm/s velocity resolution (32 velocity encodes), 12 ms temporal resolution (43 cardiac phases), 5 axial slices, 146-second acquisition per slice (256 heartbeats at 105 bpm). Reconstruction was performed in MATLAB using using the non-uniform FFT toolbox by Fessler JA.

Search for sparse representations *Methods:* Evaluated transforms included Fourier, cosine, finite differences, and several wavelet transforms, combined in various form along the five dimensions. For each evaluated combination of separable transforms, the coefficients were sorted in descending order of energy. The cumulative sum of the energy coefficients was calculated, and then normalized to 100% of the dataset's energy. Based on these curves, we assessed the sparsity of each representation, searching for those with the fastest approach to 100% of the energy. *Results:* Figure 1 shows curves of **energy vs. number of coefficents** for the two best representations (inset) among those evaluated (under our criterion for sparsity), and for the non-transformed data (blue curve). The green curve refers to a combination of Daubechies 2 (along x,y) and Haar (along z,t) wavelets. The red curve refers to a combination of biorthogonal 3.1 (along x,y,v) and Haar (along z,t) wavelets.

Qualitative evaluation *Methods:* For the two representations highlighted above, we reconstructed the image domain data from only the 1% or 0.1% largest transform coefficients. *Results:* Figure 2 compares the results for these two representations, for a voxel selected at the right carotid bifurcation (healthy volunteer). Although the results in Fig. 1 suggest that the representation using bior3.1+Haar was more promising, from this experiment we found that the representation using db2+Haar provided better results, including a denoising effect for the 1% results. Using only 0.1% of the coefficients, db2+Haar still outperforms the bior3.1+Haar representation, but significant artifacts arise.

Conclusion We evaluated several combinations of separable sparsifying transforms for FVE data of the carotids. Two very promising represantions are proposed. These were able to efficiently sparsify the evaluated data, with no significant loss of diagnostic information using only 1% of the transformed coefficients. Using a combination of Daubechies 2 (along x,y) and Haar (along z,t) wavelets, no artifacts were observed, and a denoising effect was realized. This representation should be further evaluated for other sets of data (e.g., patients, cardiac). Nevertheless, these results are an important first step towards fulfilling the great potential of CS acceleration for FVE imaging.

References [1] Moran PR. MRI 1:197, 1982. [2] Carvalho JLA et al. MRM 57:639, 2007. [3] Carvalho JLA et al. MRM 63:1537, 2010. [4] Frayne R et al. MRM 34:378, 1995. [5] Tang C et al. JMRI 3:377, 1993. [6] Carvalho JLA et al. ISMRM 15:588, 2007. [6] Lustig et al. MRM 58: 1182, 2007. [7] Gamper U et al. MRM 59:365, 2008.

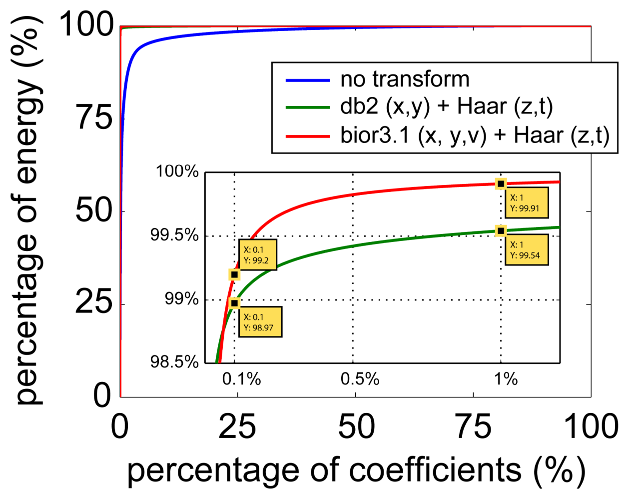

Fig.1: Curves of energy vs. number of coefficents for the two best representations (inset) among those evaluated, and for the non-transformed data (blue curve). The green curve refers to a combination of Daubechies 2 (along x,y) and Haar (along z,t) wavelets. The red curve refers to a combination of biorthogonal 3.1 (along x,y,v) and Haar (along z,t) wavelets.

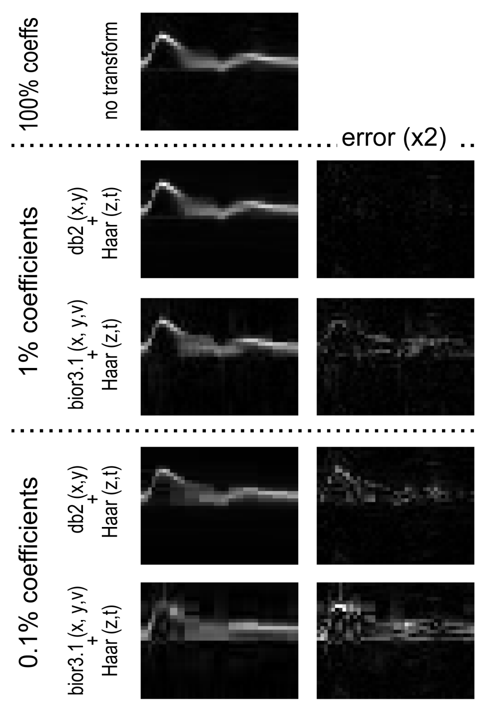

Fig. 2: FVE velocity distributions for a voxel at the right carotid bifurcation of a healthy volunteer, reconstructed from only the 1% or 0.1% largest transform coefficients. The two representations highlighted in Fig.1 are compared.