Compressed Sensing for Multiple Mouse Whole Body MRI

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Introduction In live multiple mouse whole body imaging, the heart is not the main focus of investigation yet it still presents the usual imaging problems. If the heart is to be resolved temporally by retrospective cine reconstruction, then the spatial resolution of the overall data set must be limited due to the available scan time. Conversely, at the desired spatial resolution of 100-200 um, the number of temporal samples will be restricted and interpolation error will blur the myocardium. In this abstract we consider the application of compressed sensing to reduce the data acquisition requirements and improve the image reconstruction quality in the myocardium in multiple mouse whole body imaging.

Theory Compressed sensing [1] can reduce data acquisition requirements in cases where data are intrinsically sparse and where sampling has been performed quasi-randomly. While k-space data are not normally thought of as sparse, the x-f transform space of a dynamic k-t acquisition can show a significant sparsity if the moving object (ie the heart) fills only a small portion of the spatial field-of-view.

In going from 2D human cardiac imaging to 3D mouse whole body imaging, a sizeable advantage is gained through increased sparsity, as suggested in [1]. For typical dimensions in the mouse, we expect to see sparsity of ~ 1/20. At the same time however, the computational cost of reconstruction does not scale well from 2D to 3D. The orthogonal matching pursuit algorithm (OMP) [2], which is less exact and thus faster than the alternative of convex optimization, has approximate cost for each readout point of O(d^2.8*log(d)), with d=Ny*Nz*Nt, sparsity ~ 1/20, and 3-fold undersampling (based on empirical calculations in Matlab).

A possible approach for mitigating computation cost is to divide the mouse body into two reconstruction zones along the long axis (ie readout axis) and use OMP only in the central thoracic region where the heart is located. This approach can only work if the undersampling is shifted entirely into the temporal domain, rather than in the spatial domain as described in [1].

Methods A 64x64x64 3D simulation dataset with 20 temporal frames was prepared to test the OMP algorithm on conditions of 1/20 sparsity and temporal undersampling. OMP reconstructions were performed at 3-fold randomized undersampling, both with no noise and with SNR=15 and 30. For comparison, the same datasets with 3-fold non-randomized undersampling were reconstructed by linear interpolation in the temporal domain [3].

Results In figure 1, one slice of the simulation object is depicted along the top row at every other temporal phase. It has time-varying compression, translation and contrast. In the main part of the figure, the reconstructions for the same slice are compared against the original data at three noise levels and at 3 of the 20 temporal phases. In table 1, the mean percentage error in signal intensity for blood and myocardial ROI's across all 20 reconstructed frames is given.

The OMP reconstruction is nearly exact in the noise-free case (fig 1, column 1) but less so in the presence of noise (columns 2,3). This follows expectation as noise conflicts with the assumption of sparsity. However, the result is still superior to linear interpolation, and, there is no noise amplification in the OMP reconstruction at this level of sparsity and undersampling.

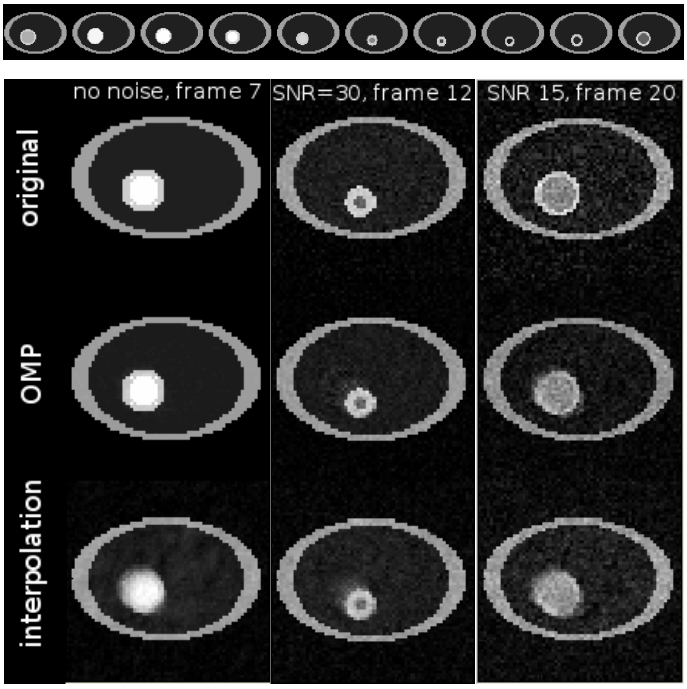

Figure 1: Reconstruction results for 3 of 20 phases and at different noise levels. The top row shows one slice of the simulation object at every 2nd time frame.

Conclusions We have demonstrated by simulation that the OMP algorithm can be applied to datasets having sparsity and undersampling characteristics of live whole body mouse MRI. Furthermore, we have shown that temporal rather than spatial undersampling may be employed. The results are sufficiently promising for application in multiple mouse MRI to warrant further study of the computation cost.

Table 1: Mean percentage signal intensity error

	SNR=30		SNR=15	
	blood	myocardium	blood	myocardium
OMP	19.1	8.9	22.8	15.1
Interpolation	37.6	15.9	37.8	15.8

References

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