

# Incorporating self-referenced information into Compressed Sensing in dynamic imaging

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**Introduction:** Compressed sensing (CS) is a newly developed fast imaging technique aimed at robustly recovering image data from partially-sampled k-space data.[1, 2] The Orthogonal Matching Pursuit (OMP) was suggested for solving medium-sized CS problems [3]. As OMP requires precisely sparse data to operate on, previous work employed a combination of constrained random sampling in k-t space along with a penalty function to improve reconstruction, in the context of dynamic MR imaging. In previous work, the penalty function was obtained by performing a first pass through the reconstruction algorithm, by estimating the density of non-zero pixels in the reconstructed result. Subsequently, this density map gets used into a second and final pass through the reconstruction algorithm, along with the original undersampled data (OMP + Density Penalty). While this approach is sound, long processing time is a main limitation of the CS approach and having to perform the reconstruction twice compounds the problem.[1]

In order to shorten computation time, an alternative scheme is proposed here that involves using the fully sampled central k-space data to generate a ‘self-referenced’ penalty function (self-referenced OMP). As a result, there is no need for an extra OMP processing to estimate the penalty function, as it has been obtained instead at the acquisition stage. Furthermore, as demanded by CS, this sampling scheme also satisfies the Uniform Uncertainty Principle for compressive sampling, a fundamental requirement of CS, hence the central fully sampled data can also be incorporated into the reconstruction. As a further benefit of our proposed approach, the more densely sampled central region can also help reduce signal interference and improve reconstruction. The need to increase density near k-space center while keeping the acceleration unchanged does however lead to a small decrease in density in outer k-space regions, which might translate into spatial blurring.[1]

**Methods:** The constrained random sampling function in k-t space (Fig 1a) was generated according to the procedure described in Ref[2]. The central 10% of k-space was then fully sampled for every time frame, as depicted in Fig 1b. This central region was used to produce low spatial resolution reference images  $\mathbf{F}$  and the penalty function for the OMP algorithm was defined as  $\mathbf{F}^m$ , where the exponent  $m$  was introduced as an adjustable weighting parameter to feature the sparse peaks. The OMP reconstruction starts from the aliased y-f signal  $\mathbf{A}$  and the peak signal in  $[\mathbf{F}^m * \mathbf{A}]$  is selected and added to the final reconstructed data  $\mathbf{I}$ . Then the new residual aliased signal  $\mathbf{A}$  is calculated by subtracting the convolution of the point-spread function to the recovered signal  $\mathbf{I}$  from aliased signal of the former step. This procedure is repeated until the stop criterion is reached. In the following experiments, we stopped the iteration when the maximum residual signal reached a level below 1/10000 of the first selected peak, and 0.3 proved to be a reasonable setting for  $m$ . The previously proposed approach, with two passes through the reconstruction, was also implemented for comparison.

Full datasets from two different dynamic applications, cardiac cine and fMRI, were subsampled and used to test the CS algorithms. Volunteer cardiac cine imaging using ECG triggered bSSFP sequence was performed on a GE Signa 3T scanner (matrix size=192x160, flip angle = 45°, TR=3.5 ms, TE=1.7ms, 24 cardiac phases). The SSFP fMRI dataset was acquired with frequency stabilization on a 3T Philips Achieva magnet [4]. The functional task employed two cycles of block-designed visual stimulation with flickering checkerboard images displayed. Each cycle began with a 20-sec resting phase showing a black screen, followed by a 20-sec visual stimulation. The imaged temporal resolution was 2 seconds. The cardiac and fMRI datasets were subsampled by factors of 3 and 4, respectively, to simulate acceleration.[1]

**Results and Discussion:** Figure 2 shows the fully acquired cardiac results, along with both CS results (proposed scheme – self-referenced OMP, and previously published scheme – OMP+Density Penalty). No significant spatial artifact or noise amplification could be detected in the results from either CS approaches. Both methods exhibited temporal blurring as compared to the original dataset. Slightly more spatial and temporal smoothing was noticed using the self-referenced OMP scheme.

The fMRI results analyzed by SPM5 are illustrated in Fig 3. The voxels having FWE corrected p-value less than 0.05 were identified as activation sites corresponding to the given stimulation. An extent threshold of three voxels was also applied to exclude the small cluster. The activation maps were superimposed to the first frame of each reconstructed image series. In terms of the overlaid image, no significant artifacts could be noticed. The activation regions were all located in the visual cortex and only slight differences in cluster size were measured. With respect to temporal signal, for the self-referenced OMP results, temporal signal changes were similar to the original data. On the other hand, the result of “OMP+Density Penalty” shows a smoothed curve. Although the principal frequency components seemed to be retained in “OMP+Density Penalty”, the spurious changes were missing and the signal difference between resting and stimulated phases also decreased.

A method that incorporates self-referenced information into a Compressed Sensing solution was introduced, to reduce computation time by roughly a factor from 1.4 to 2. While the increased sampling density near k-space center and decreased density in outer k-space regions may have caused some spatial blurring, the present results suggest our method may retain more temporal information in the context of fMRI experiments.

**References:** [1].Lustig, M., et al., *Magn Reson Med*, 2007.p.1182-95 [2].Gamper, U., et al., *Magn Reson Med*, 2008.p.365-73 [3].Tropp, J.A., et al., *IEEE TIT*, 2007.p.4665 [4].Wu, M.L., et al., *Magn Reson Med*, 2007.p.369-79

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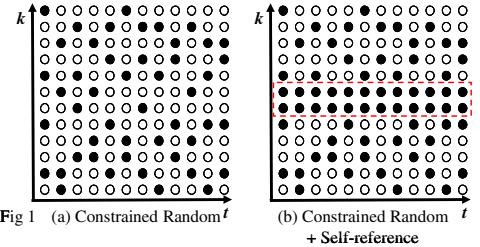


Fig 1 (a) Constrained Random  $t$   
(b) Constrained Random + Self-reference

