

# Combination of Compressed Sensing and Parallel Imaging with Adaptive Motion Compensation for Accelerated Dynamic MRI

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**INTRODUCTION:** Compressed sensing and parallel imaging has been shown to be useful in accelerated acquisition of dynamic MRI especially when temporal correlations are exploited by sparsifying temporal transforms [1]. More sophisticated methods to further exploit temporal dependence in the data has been proposed which borrows from approaches used in video compression [2-3]. However, as in video coding applications, these methods need a reference frame and/or fully sampled low pass part of the k-space data which may not be available in practice. In this work we present an adaptive method, which combines the motion estimation and signal regularization steps and jointly estimates both the motion and signal without need for reference frames, fully sampled partial k-space data or an explicit model for the motion except smoothness criteria.

**THEORY:** In compressed sensing, missing parts of a measured signal are recovered by making use of prior information such as that signal being sparse in a transform domain. It is also not uncommon to use analysis priors such as total variation (TV) to regularize the signal in compressed sensing reconstructions. In order to improve exploitation of the temporal dependence in the signal, we define a generalized version of total variation called *Motion-TV* as:

$$\text{Motion-TV}(x) = \sum_{i=1}^{n_t} |x_i(s + v(s)) - x_{i-1}(s)|_1 = |M_v x|_1$$

where  $s$  is the spatial index,  $x_i$  is  $i^{\text{th}}$  temporal frame of the signal. Note that this is equivalent to TV in temporal direction when  $v$  is zero. Therefore given a motion field  $v$ , the signal can be reconstructed by solving

$$x^* = \arg \min_x |M_v x|_1 \quad \text{s.t.} \quad \|y - Hx\|_2^2 < \epsilon$$

where  $H$  is the transfer function of the parallel MRI with subsampling and  $y$  is the subsampled measurements. This solution can be found by iterative algorithms such as MFISTA or Augmented Lagrangian based methods. In dynamic MRI problems the signal might deform in time, motion of which can be estimated by deformable registration methods such as Demon's Method [4] which are also iterative. In our proposed method these iterations are joined together in a single algorithm to estimate both motion and the signal utilizing the prior that the motion field is smooth.

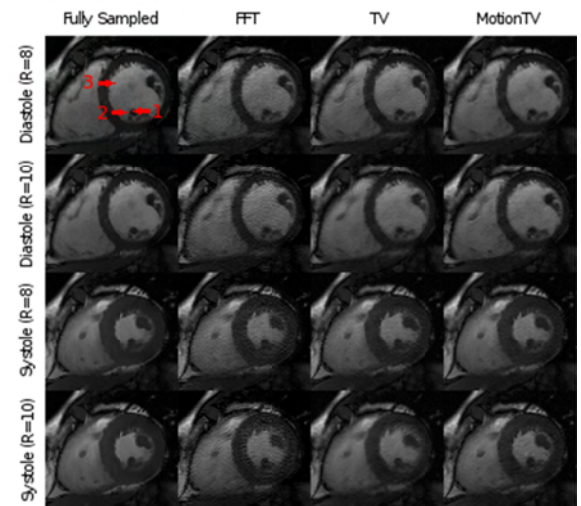
**METHODS:** 2D cardiac cine imaging was performed on a 3T Siemens Trio scanner using a standard 12-coil matrix body array. Fully-sampled data were acquired using a  $256 \times 256$  matrix (FOV =  $320 \times 320$  mm<sup>2</sup>) and 24 temporal frames and retrospectively undersampled by a factor of 8 and 10 using a different variable-density random undersampling along  $k_y$  for each time point. An Augmented Lagrangian based method is used for optimization and motion is estimated from a denoised version of the estimate for the signal at each iteration. The algorithm converges at a similar speed with temporal TV or temporal FFT minimization with approximately 15% increase in processing time due to motion estimation.

**RESULTS:** *Motion-TV* reconstruction is compared to results with k-t SPARSE-SENSE with FFT [1] as well as results with temporal TV minimization. *Motion-TV* based reconstruction is shown to have better quality (Fig. 1) and temporal clarity (Fig 2) compared to the other methods especially at very high acceleration. This is due to temporal FFT and temporal TV being limited to temporal correlations within every pixel while *Motion-TV* makes use of spatio-temporal correlations among different pixels in an efficient manner. This helps avoiding temporal blurring which occurs with temporal-only methods at high acceleration rates. It also keeps spatial blurring at a minimum as opposed to spatial transforms such as wavelets.

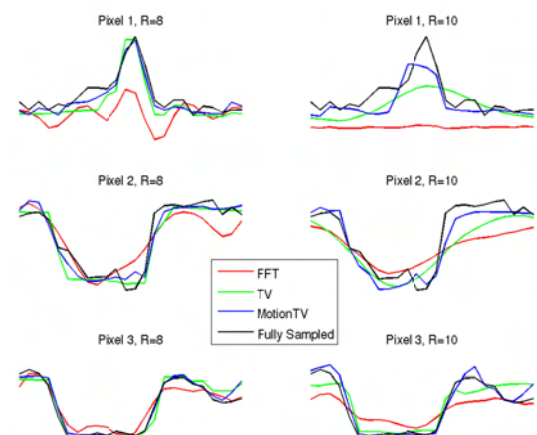
**DISCUSSION:** An efficient method that enables signal reconstruction exploiting spatio-temporal redundancy by adaptively estimating the motion was presented. The algorithm does not need any additional priors such as reference frames or motion model except the assumption that the motion field is smooth. Spatio-temporal regularization enables reconstruction at very high acceleration rates at the expense of a fraction of total processing power. Future work includes experimenting with different data types and scenarios.

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**REFERENCES:** [1] Otazo R et al. Magn Reson Med. 2010;64(3):767-76. [2] Jung H. et al. Magn Reson Med. 2009;61(1):103-16. [3] Jung H. et al. ISMRM 2009 [4] Vercauteren T. et al NeuroImage 45(1) 61-72 2009



**Fig. 1:** Reconstruction of 8-fold and 10-fold undersampled data using k-t SPARSE-SENSE with FFT, temporal TV minimization and MotionTV minimization, The red arrows indicate pixel locations at high motion areas which are shown in Fig. 2.



**Fig. 2:** Temporal changes of different pixels when reconstructed with different priors at rates R=8 and R=10. The pixel points are shown in Fig. 1