New Physically Plausible Compressive Sampling Schemes for High Resolution MRI at 7 Tesla

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Abstract-Please add a very brief abstract here (max 150 words).

I. INTRODUCTION

Magnetic Resonance Imaging (MRI) data are collected in the k-space (spatial Fourier domain) along regular trajectories which are subject to kinematic constraints. Indeed, the gradient waveforms which are responsible for this displacement in k-space are obtained by energizing gradient coils with electric currents, whose amplitude and slew rate are upper bounded. Since high resolution MR imaging requires visiting larger k-space domains (i.e., larger k_{\max}), collecting such data is time consuming.

On the other hand, MR image resolution improvement in standard scanning times (e.g., 200 μ m in-plane in 15 min) would allow neuroscientists and doctors to push the limits of their current knowledge and to significantly improve both their diagnosis and patients' follow-up. One critical path to achieve this goal relies on the Compressed Sensing (CS) theory [1], [2], which has revolutionized how data can be collected in a compressed manner while ensuring conditions for optimal image recovery. This breakthrough has been accomplished by combining three key ingredients: (i) pseudo-random acquisitions, (ii) image representation using sparse decompositions (e.g., wavelets) and (iii) nonlinear image reconstruction.

Although heuristic application of CS in MRI has provided promising results [3], CS theory cannot be directly cast to the MRI setting. The reasons are: 1) the acquisition (Fourier) and representation (wavelets) bases are coherent and 2) 2D sampling schemes obtained using CS theorems are composed of isolated measurements and cannot be efficiently implemented by magnetic field gradients. In the recent literature [4], [5], [7], variable density sampling (VDS) theory has addressed the first impediment. Moreover, in the seminal paper [3], 2D pointwise sampling was performed along parallel lines in the orthogonal readout direction to the the slices of interest, thus implementing a 2D VDS within each slice. However, in a 3D perspective, this 2D-VDS is likely suboptimal since high frequencies along the readout direction are sampled too densely, hence increasing the scanning time uselessly.

To go beyond this approach, new 2D sampling trajectories that fulfill acquisition constraints while traversing the k-space as fast as possible according to a prescribed variable density have been proposed in [8], [10]. In brief, the proposed framework consists of projecting a probability distribution (i.e. π) onto a set of measures that are brought by admissible curves with respect to the gradient constraints. The proposed iterative algorithm also allows to handle arbitrary affine constraints (e.g. echo time specification) and automatically generates efficient sampling patterns. So far, it has been implemented for 2D MRI both in retrospective and prospective acquisition scenarios. On massively undersampled (~ 5 % of full k-space coefficients) simulated data (Fig. 1), we first illustrate its impact on the SNR of reconstructed MR images as compared to other sampling schemes (radial, spiral, iid drawings). All MR images were reconstructed using a non-Cartesian implementation of the FISTA algorithm [?]. The reconstruction results obtained in simulations using this strategy outperform existing acquisition trajectories (spiral, radial) by about 3 dB. More recently, we adapted a GRE sequence to acquire a T2* weighted image of an *ex-vivo* baboon brain with our new trajectories. These results in progress proved the practical feasibility of these sampling schemes and shows promising results.



Fig. 1. $n = 2048 \times 2048$, $G_{\rm max} = 40 \ {\rm mT.m^{-1}}$, $S_{\rm max} = 150 \ {\rm mT.m^{-1}.ms^{-1}}$.

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