RFuGE –an accelerated imaging method combining Parallel Transmit RF encoding plus Gradient Encoding with compressed sensing reconstruction

M. Usman[1], S. Malik[2], U. Katscher[3], P. Batchelor[1], and J. Hajnal[2]
[1]Imaging Sciences, King's College London, London, United Kingdom, [2]Robert Steiner MRI Unit, Imaging Sciences Department, MRC Clinical Sciences Centre, Hammersmith Hospital, Imperial College London, London, United Kingdom, [3]Sector Medical Imaging Systems Philips Research Europe, Hamburg, Germany

Introduction: In compressed sensing, a problem with random phase encoding patterns is that the eddy current performance is much worse and can lead to significant artefacts because the resulting k-space distortions may be very different on adjacent k-space samples. This undermines performance in random sampling strategies. We have explored combining regular gradient sampling with randomly selected radio-frequency encoding achieved using a parallel transmit approach. This work has been stimulated by two developments: 1) constrained random sampling patterns consisting of a regular base sample distribution with a +/-1 Δk jitter has been demonstrated to perform as well as a more fully random sets of phase encodes for moderate to high sampling factors (up to 5-fold undersampling)[1][2], and 2) parallel transmit technology can provide effective spatial encoding by generating distinct RF field (B_1) patterns that impose appropriate spatial phase variations [3].

Method: Parallel transmission allows spatial control of B_1 - a degree of freedom which in the past has not been available. These RF fields can be varied to effect the phase across the object FOV. This approach could be used to achieve the performance of the jittered undersample patterns without any eddy current effects. However, the linear phase variation that corresponds to a pure shift in k-space is hard to achieve in combination with uniform flip angle and can result in greatly elevated RF drive levels, which limits the applicability of this simple extension to gradient encoding. We therefore consider a more general approach, in which a set of K distinct RF field patterns are produced that have spatially varying phase structure, uniform flip angle and low SAR. To ensure that a basis set of patterns are distinct from one another we design each around a narrow strip phase ramp with a unique direction, but allow the rest of the field of view to vary freely consistent with a uniform excitation. We then adopt a regular subsampled gradient pattern and for each gradient step apply a randomly selected choice from these RF basis functions. We call this type of encoding **RF** pl**u**s **G**radient **E**ncoding, (RFuGE) and employ a Compressed Sensing style reconstruction [4] designed to exploit the random element in the data structure. Provided the signal remains sparse in itself or in transform domain an exact reconstruction may be achieved. To proceed we construct an exact forward model of RFuGE that predicts the data given an object and knowledge of the RF basis set:

$$\begin{pmatrix} \mathbf{Y}_1 \\ \mathbf{Y}_2 \\ \cdot \\ \cdot \\ \mathbf{Y}_K \end{pmatrix} = \begin{pmatrix} \mathbf{A}_1 & & & \\ & \mathbf{A}_2 & & & \\ & & \cdot & & \\ & & & \cdot & \\ & & & & \mathbf{A}_K \end{pmatrix} \begin{pmatrix} \mathbf{F}_1 & & & & \\ & \mathbf{F}_2 & & & \\ & & \cdot & & \\ & & & \cdot & \\ & & & & \mathbf{F}_K \end{pmatrix} \begin{pmatrix} \Sigma_1 \\ \Sigma_2 \\ \cdot \\ \cdot \\ \Sigma_K \end{pmatrix} \boldsymbol{\rho}$$

$\boldsymbol{\rho}$ is the object (image) to be recovered, Y_1 Y_2..Y_K are measurements in k-space, Σ_1 Σ_2...Σ_K are the composite B_1 maps used in encoding, K being the total number of encodings used, $F_1, F_2, ..., F_K$ are the fully sampled Fourier operators, $A_1, A_2, ..., A_K$ are the sampling patterns, that decide which samples from the uniform lattice are to be sampled with composite B_1 maps Σ_1 Σ_2...Σ_K respectively. Each sampling pattern selects a unique set of samples such that union of all sampling patterns constitute a uniform lattice grid. Combining the above expressions together, we get $Y = AF\,\Sigma\boldsymbol{\rho}$

Compressed sensing reconstruction can be expressed as: $\min_x \|\mathbf{x}\|_0$ s.t $Y=AF\,\Sigma\,\Psi^*\mathbf{x}$ where $x = \Psi\boldsymbol{\rho}$, Ψ being a sparsifying transform, The above problem can be solved by l_1 minimization or the Orthogonal Matching Pursuit (OMP) method. For implementation of RFuGE, our setup was as follows:

Given a set of individual coil B_1 maps acquired from a Philips 3T Achieva scanner fitted with an eight channel parallel transmission body coil [5], a set of eight different phase variation across the object that also resulted in approximately uniform B_1 amplitude were calculated using a magnitude least squares optimisation procedure with local phase update to enforce the desired ramp on a narrow strip field of view/10 wide; the resulting phase variations of these composite B_1 maps are shown in Figure 1. The individual coil sensitivity patterns used were measured in the tranverse plane in the pelvis of a volunteer and a target image employed was a pelvis image of the same subject. We compared three types of encodings. a) **RF** pl**u**s **G**radient **E**ncoding, (RFuGE) b) gradient encoding only (jittered k-space) c) and uniform lattice gradient encoding. For RFuGE , the samples along the 1-D uniform lattice grid were encoded using the 8 composite B_1 maps such that each composite B_1 map was used to encode randomly 1/8th of the sampled k-space points. The 5 central k-space lines were encoded using one of B_1 maps (B_1 map with approximately constant phase across the image). For gradient only encoding, we used simulated 1-D jittered k-space pattern to create quasi-random under-sampling. For lattice encoding, we used the same sampling pattern as for RF plus gradient encoding. For both lattice and gradient encoding the same B_1 map was employed for every sample.
In compressed sensing reconstruction part, the reverse operator was implemented by combining individually inverted smaller subsystems. For pelvis images, we used wavelets as the sparsifying transform. Our reconstructions were based on l_1 minimization code as implemented in SPGL1[6].

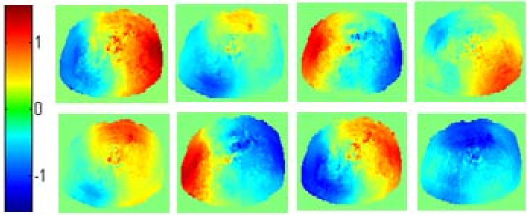
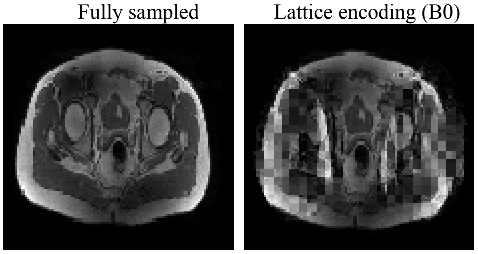


Fig. 1: Phase variation of eight composite B1 maps used in RFuGE encoding


Fully sampled
Lattice encoding (B0)

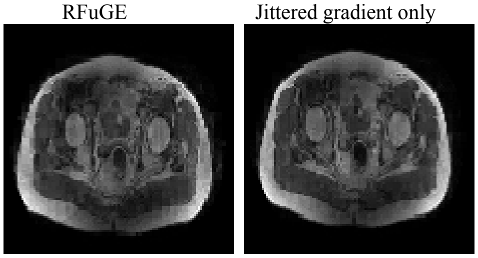

RFuGE
Jittered gradient only

Fig.2: Compressed Sensing Reconstruction with different encodings

Results: The results for a 1D undersampling factor of 2 are shown in Fig.2. The under-sampling is done along the horizontal direction. For RF plus gradient encoding, and the jittered gradient encoding only, the reconstruction was nearly exact. Substantial errors occur in the pure lattice sampling case. Fig 3 shows difference images corresponding to Fig 2.

Conclusion-Discussion: We have demonstrated the feasibility of using parallel transmit to encode an additional jitter onto regularly undersampled Gradient Encoding. This RF plus Gradient Encoding (RFuGE) algorithm is a combination of novel use of hardware together with modern reconstruction techniques beyond the Nyquist limit. RFuGE has the potential to avoid undesirable gradient switchings required for random undersampling and introduces greater potential flexibility through use of a non-linear encoding scheme.

Spatial encoding is at the core of MR *Imaging*. The standard Fourier encoding has been extremely successful, but acquisition times are ultimately limited by Shannon's theorem. Compressed Sensing MRI opens the door to faster imaging, but standard CS MRI with Phase Encode Fourier undersampling has its own issues. This abstract demonstrates how hardware and reconstruction improvement *together* can offer extra potential benefits.

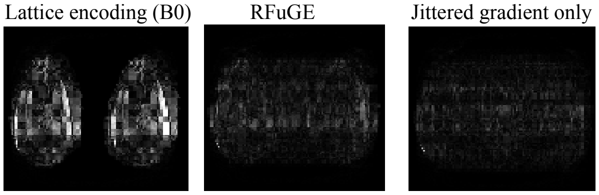

Lattice encoding (B0)
RFuGE
Jittered gradient only

Fig.3: Reconstruction Error images with different encodings

References: [1] Gamper et al. Magn. Res. Med. 59,365-373, 2008 [2] M. Usman et al, Proc. ESMRMB, vol. 25, P. 344, 2008 [3] U. Katscher et al, Proc. ESMRMB, vol. 25, p 97, 2008 [4]M. Lustig et al, MRM, 58(6):1182-1195, 2007 [5] P. Vernickel et al, MRM, 58:381–389, 2007 [6] E. Berg, http://www.cs.ubc.ca/labs/scl/spgl1