A GA Guided K space Sampling for Compressed Sensing MRI

Introduction: Compressed sensing (CS) has been applied to MRI to exploit the acquisition redundancy so that the imaging can be accelerated in many speed demanding scenarios such as dynamic imaging, volume imaging etc., based on the fact that compressible signals can be reconstructed from randomly under-sampled frequency information [1,2]. CS variants, especially those employing the parallel imaging (PI) techniques, have been proposed in the aim to reduce the scan time further and ameliorate various image artefacts [3,4] with a fixed k-space sampling pattern. Another group of studies explored optimal sampling patterns [5,6], so that further reduction factor can be achieved, while still maintaining the incoherence between the sparsity basis and the measurement matrix. In this work, a Genetic Algorithm (GA) guided gridded variable density function is applied to redistribute the random sampling, with the aim to improve image quality.

Method: CS reconstruction has two fundamental requirements: (a) the imaging object is compressible to a large extent within a sparse transform; (b) the measurement matrix is incoherent to the sparsity transform basis. The sparsity and incoherence between the transform basis and measurement matrix thus determine the possible under-sampling rate, i.e. fast imaging performance. Considering the k-space resolutions, it is computationally not practical to configure the measurement matrix with the optimal sampling scheme, which will achieve maximized incoherence. However, to bring this idea into close reality, the problem space can be ideally reduced, so that a sub-optimal solution in this regard can still be achieved. In this work, a tiled style variable density function was implemented to distribute the random sampling in limited grids as shown in Figure 1 left. Each grid was assigned a weighting factor, so that the density distribution can be adjusted individually. The CS reconstruction then presents a non-linear problem with the distribution of weighting factors as variables. Then, this function is to be optimized by applying GA to search for sub-optimal solutions of the weightings. Initial set of L population are generated randomly, but still with centre k-space area intensively populated. The weighting distribution of tiled density function grids is then encoded in binary form as chromosome of size LxB where B is the number of bits for each weighting. To evaluate the behaviour of the population, peak signal-to-noise-ratio (PSNR) was chosen as the fitness function, which represents the ability to survive of each chromosome, i.e. k-space sampling patterns. In an iterative manner, once the reproduction process is finished with fitness-weighted selection, crossover and mutation are implemented. Thus the next generation are produced for the next iteration. Both a fixed iteration number and convergence measure of PSNR were chosen as the termination conditions. By then, the sub-optimal sampling pattern is generated according to the weightings of the grid variable density function. Figure 1 right shows the iterative procedure of this method.

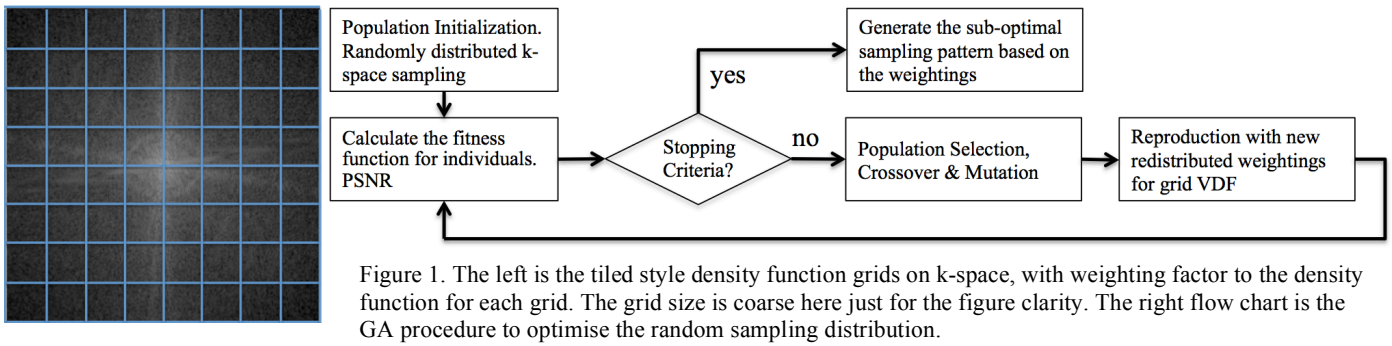

Figure 1. The left is the tiled style density function grids on k-space, with weighting factor to the density function for each grid. The grid size is coarse here just for the figure clarity. The right flow chart is the GA procedure to optimise the random sampling distribution.

Results and Discussion:

A T2 weighted brain image was used to evaluate performance of this method against the conventional Gaussian distributed random sampling scheme. The image was also synthesized with a 5% Gaussian noise to mimic real case. Figure 2 illustrates the proposed method can provide better image quality in the framed region with sharper details. The sampling rates of these two methods were 5.5 and 5 respectively. Figure 3 shows the reconstruction comparison with a 3D apple, imaged on a 9.7T system. The sampling pattern was optimized to investigate the performance of this method in 3D k-space. PSNR was plotted over 200 image slices along the apple axis. An averaged 4.2 to 5.8 dB higher PSNR was observed, showing better imaging quality was achieved by this method. The reduction factors of this sampling method and conventional method were set to 5.5 in this case. It also illustrates that the proposed method have even more potentials on 3D case, where the sampling scheme have more freedom to search for optimised solutions.

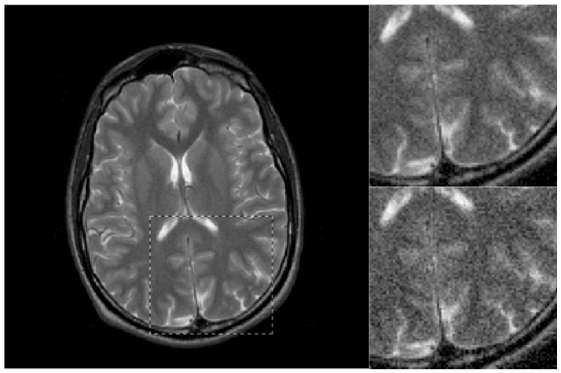

Figure 2. The left is a T2 weighted brain image. The right are reconstructed images by the proposed method (up) and the conventional method (bottom) respectively with localized view of the framed region.

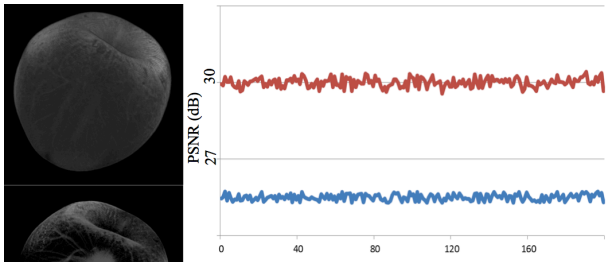

Figure 3. The left are plots of the 3D apple with different transparency. The right is the plot of PSNR achieved by the proposed method (red), conventional method (blue).

Conclusion: In this work, we presented a method to optimise the k-space sampling scheme for CS-MRI. The problem was simplified by treating the variable density functions in parts, and optimising the weighting factors with GA. Future work will look for solutions to improve this procedure, so that an experimental side validation can be possible with the generated sampling patterns.

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References: [1] Lustig M *et al*, *MRM,* 58, 2007. [2] Sebert F *et al, Proc. ISMRM*, 3151, 2008. [3] Liu B *et al*, *Proc. ISMRM*, 3154, 2008. [4] Wu B *et al*, *Proc. ISMRM*, 1480, 2008. [5] Ravishankar S *et al, IEEE EMBS*, 2011. [6] Lai P *et al, Proc. ISMRM* 68, 2010.