Ming Hsieh Department of Electrical Engineering

USC Viterbi School of Engineering

Brain DCE MRI with direct estimation of pharmacokinetic parameters from highly undersampled (k,t)-space

Yi Guo, Yinghua Zhu, Sajan G. Lingala, R. Marc Lebel, Krishna S. Nayak

Magnetic Resonance Engineering Laboratory

Introduction: In T1-weighted dynamic contrast enhanced (DCE) MRI, pharmacokinetic (PK) maps (K^{trans}, abbreviated K_t, and v_p, etc.) are derived from the dynamic image series and used for diagnostic purpose. In accelerated DCE MRI, anatomic image series are typically reconstructed from under-sampled k-space first, then fit into a PK model to derive the parameter maps [1]. As the PK parameters have much less dimension than the original multi-coil k-space, direct estimation of PK parameters will promote higher acceleration and save the resources estimating all the intermediate steps. Recently, Dikaios *et al* [2] have used a Beysian inference framework to directly estimate PK maps from under-sampled k-space and achieved 8x acceleration in phantom and prostate cancer data. In this study, we propose a novel and efficient optimization approach to directly reconstruct the PK parameters from highly under-sampled k-space, and show that whole-brain DCE, with up to 30x acceleration rate, can be achieve through this method.

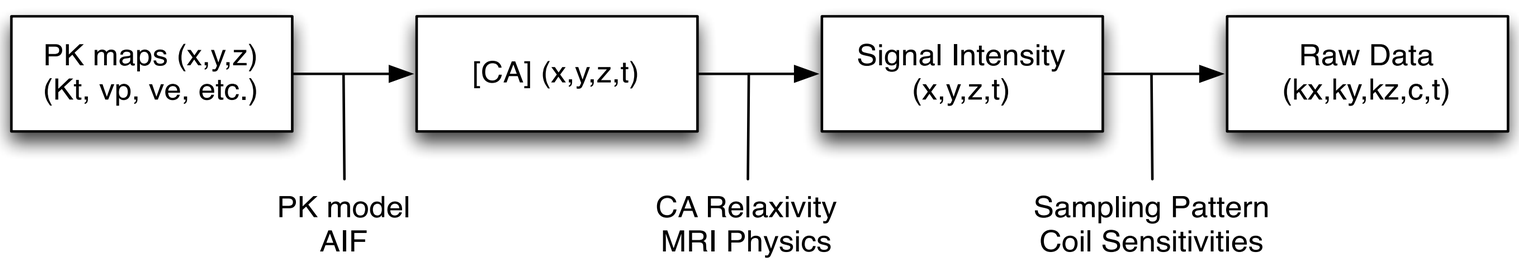

Fig 1 Flowchart of the forward modelling

Methods: Fig 1 demonstrates the forward modelling of the PK parameters, where a Patlak model was used in this study. The PK parameters (K_t, v_p) are related to the acquired under-sampled k-space data (k_u) as the steps in table1.Thus, a model-based reconstruction is to solve (K_t, v_p) from k_u by the following least-square optimization problem:

$$(K_t, v_p) = \arg\min_{K_t, v_p} \| k_u - F_u S \varphi(P(K_t, v_p) \cdot \Re 1 + R_0) \|_2^2 + \| \psi K_t \|_1 + \| \psi v_p \|_1 \qquad (1)$$

, where sparsity is enforced by l1 norm constraints in the wavelet transform (Ψ) domain of the PK parameters as indicated Eqn 1. This nonlinear optimization problem is then solved by a quasi-newton limited-memory Broyden–Fletcher–Goldfarb–Shanno (L-BFGS) method.

A fully-sampled DCE data set from a brain tumor patient is acquired in a 3T GE scanner. The data set is retrospective under-sampled 30x by a Poisson-disc under-sampling pattern, then the proposed model-based reconstruction is used to calculate the PK maps directly from the under-sampled k-space. The PK maps are also estimated using images from fully-sampled and zero-padding k-space for reference.

Table 1 Steps to model PK parameters (K_t, v_p) to under-sampled k-space (k_u)

1. The K^{trans}(K_t) and v_p are fitted to the contrast concentration(CA(t)) over time, where $C_p(t)$ is population-based AIF from Ref [3]:
$CA(t) = P(K_t, v_p) = K_t \int_0^t C_p(\tau)\,d\tau + v_p C_p(t)$
2. CA(t) is related to the changes in T1 relaxation rate over time(R1(t)): where $\Re 1$ is 4.39 $s^{-1}mM^{-1}$ for gadolinium, R_0 is the pre-contrast R1 maps calculated from T1 mapping sequence before DCE:
$R1(t) = CA(t) \cdot \Re 1 + R_0$
3. R1(t) is related to the signal intensity S(t) by the general signal equation, where TR is the repetition time, α is the flip angel, M_0 is the equilibrium longitudinal magnetization that is acquired from T1 mapping sequences:
$S(t) = \varphi(R1(t)) = \frac{M_0 \sin\alpha(1 - e^{-TR \cdot R1(t)})}{1 - \cos\alpha e^{-TR \cdot R1(t)}}$
4. S(t) is related to the under-sampled k-space (k_u) by coil sensitivities(S), and under-sampling Fourier transform(F_u):
$k_u = F_u S(S(t))$

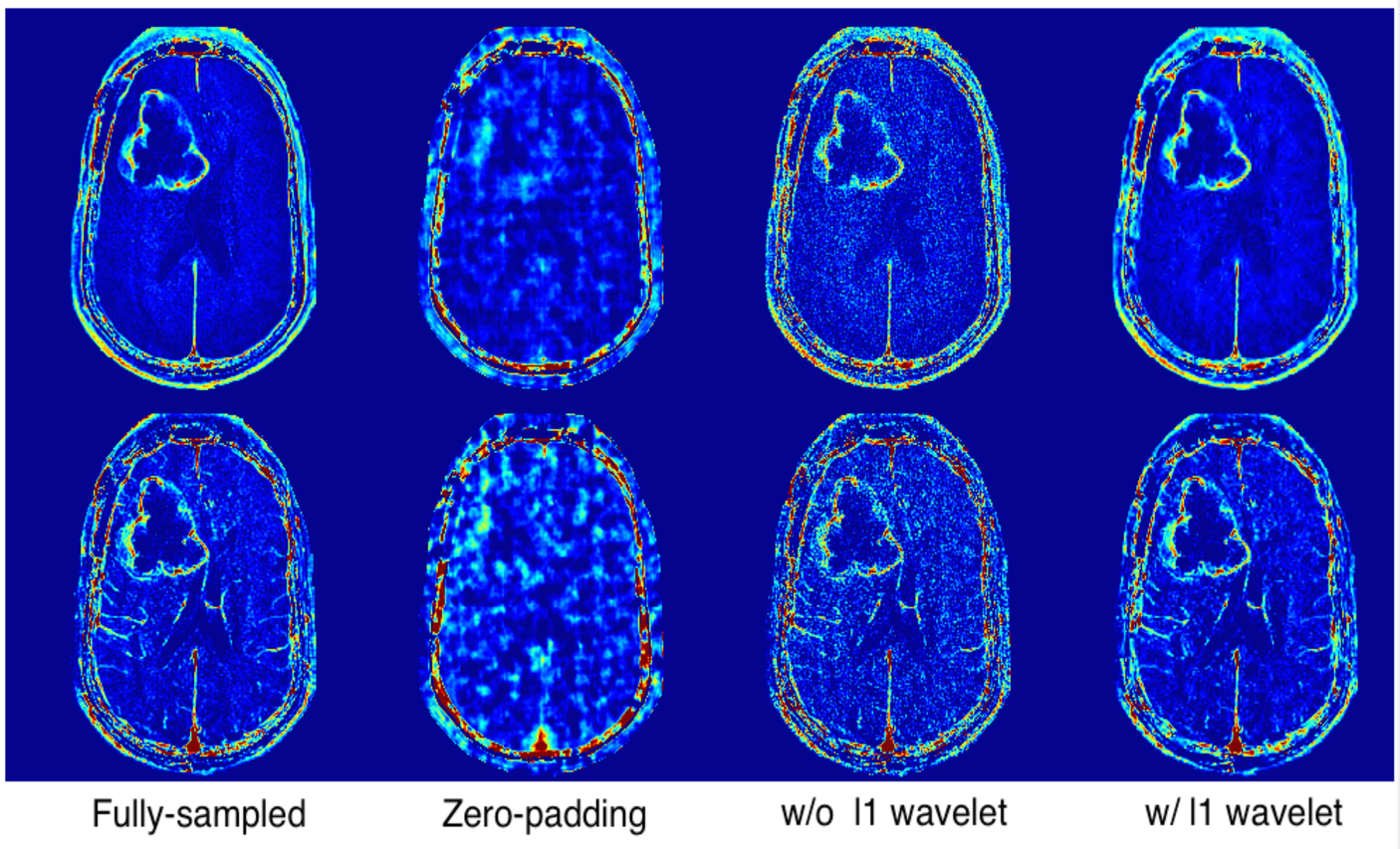

Fig 2 Model-based reconstruction results (w/o or w/ l1 wavelet constraint) from under-sampled (30x poisson-disc sampling pattern) k-space.

Results: Fig 2 shows the results of this model-based reconstruction for a glioblastoma patient. As it is shown, by simply enforcing the PK model in the reconstruction, the results are greatly improved compared to the PK parameters estimated from zero-padding images. By adding a wavelet sparsity constraint, the noise is further removed and the quality is comparable to the fully sampled results.

Conclusion: In this study we have proposed a novel reconstruction method to directly estimate PK parameters from under-sampled k-space, and show that it can accurately restore PK values from highly under-sampled data, while saving the resources and time to estimate all the intermediate images.

References: [1] R. M. Lebel, MRM 71(2): 635–644, 2014 [2] N. Dikaios, Medical Image Analysis 18:989-1001, 2014, [3] G. Parker, MRM 56:993–1000, 2006 [4] M. Lustig, MRM *58*(6), 1182-1195, 2007. [5] Mark Schmidt: http://www.cs.ubc.ca/~schmidtm/Software/minFunc.html

Contact: Yi Guo, yiguo@usc.edu