Direct parametric reconstruction from (k, t)-space data in dynamic contrast enhanced MRI

Nikolaos Dikaios[1], Shonit Punwani[2], and David Atkinson[2]
[1]*Centre of Medical Imaging, UCL, London, United Kingdom,* [2]*Centre of Medical Imaging, UCL, Greater London, United Kingdom*

Purpose: Direct parametric reconstruction (DPR)[1], offers a new perspective in MR, setting the model parameters as the aim of reconstruction by estimating them directly from k-space using a Bayesian inference algorithm. DPR was implemented to derive model parameters from dynamic contrast enhanced (DCE) (k,t)-space data i.e. plasma volume v_p, extracellular extravascular volume (EES) v_e, transfer rate between plasma and EES (min^{-1}) K_{trans}[2].. Its performance was evaluated against the current "indirect" approach where (k,t)-space DCE data are reconstructed (either with a Fourier Transform or with kt-FOCUSS[3] when undersampling was present) to images and then fitted using a pharmacokinetic (PK) model[2]. The purpose of this work is to address some previous limitations of the DPR algorithm, namely the suggested modifications are to jointly reconstruct proton density, ρ and native T1 map (T10), from the data and to account for different pharmacokinetic (PK) models in different tissues.

DPR: In the suggested implementation ρ and T10 are initially estimated directly from multiple flip angle data, and are updated during the estimation of the PK parameters from both the multiple flip angles and the DCE k-space. The previous implementation[1] described enhancement of all tissues using the modified Toft model[2], which is not appropriate for certain tissues. For example the enhancement of the liver requires a dual input model (both arterial and portal input). To select the appropriate PK model per tissue, DPR (with less iterations) is initially run for different PK models (i.e. flow model, Toft model, modified Toft model, Liver model[4]) and a likelihood function derived per PK model. The PK model with the smallest number of parameters that provide an acceptable likelihood (above a certain threshold) was selected, providing a binary mask per PK model. The acceptable likelihood threshold was decided semi-automatically based on a comparison of the likelihood maps of the PK models and visual inspection of the PK model masks. DPR was then run using the PK model binary masks as prior information.

Methods: Simulated abdominal DCE (**k**, t)-data were generated as described by[1] with the difference that the enhancement in the liver is now modelled using the Orton[4] PK model. In addition, multi-flip angle k-space data were generated at different flip angles 5°, 10°, 15 °, 20 °, 25 °, 30 °, 35°. Ground truth parametric maps i.e. ρ (range 0-16287), T10 (range 0-1.55 sec), v_p (range 0-1), v_e (range 0-1), K_{trans} (range 0-1.38 min^{-1}) and the arterial–venous fraction γ (range 0-0.74) of the Orton model are compared to the ones derived from DPR using the root mean square error (rmse).

Results: Figure 1 describes the current implementation of DPR. The results shown are for fully sampled k-space. Initially DPR runs for the multi-flip angle k-space data, to derive ρ and T10. The correspondence of ρ and T10 to their ground truth values is rmse= 140 and 0.12 respectively. The algorithm is then run to create a binary mask for each PK model, the percentage of correct assignments is 96% for the "flow" model, 60% for the Toft model, 98% for the Orton and 83% for the modified Toft model. The derived binary masks are subsequently used as prior information in DPR to jointly reconstruct ρ, T10, v_p, v_e, K_{trans} and γ from both the multi flip angle and DCE k-space data. The respective rmse were 115.6, 0.10, 0.02, 0.37, 0.07, and 0.02. Note that the joint estimation of all model parameters improved the correspondence of ρ, T10 to their ground truth values by 18% and 16% respectively.

Limitations: The proposed implementation of DPR has not been evaluated on undersampled data or when motion is present. Both motion and undersampling could affect our ability to accurately assign each pixel to the appropriate PK model. Further the enhancement in the heart has been simulated by just using plasma volume. Future work on the selection of undersampling pattern, low-rank/sparsity priors, motion compensation and the automatic selection of PK models could be undertaken.

Conclusions: DPR as initially suggested by[1] has shown promising results especially for high undersampling but had limitations, some of which we tried to address in this work. The current implementation suggests a joint reconstruction of all model parameters related to DCE, and has the ability to select the appropriate PK model for each pixel. The model selection is a non-trivial step as we simultaneously need to avoid over-fitting (by using more model parameters than needed) and accurately describe the kinetics. DPR might easily be applied to Diffusion Weighted MR, where due to the presence of noise especially at high b-values we expect DPR to outperform current techniques.

Acknowledgements: This work was undertaken at UCLH/UCL, which receives funding from the Department of Health's NIHR Comprehensive Biomedical Research Centre funding scheme. This work was supported by UK EPSRC; Grant numbers: EP/I018700/1, EP/H046410/1 and the joint CR-UK & EPSRC funded King's College London and UCL Comprehensive Cancer Imaging Centre, in association with the MRC and DoH (England).

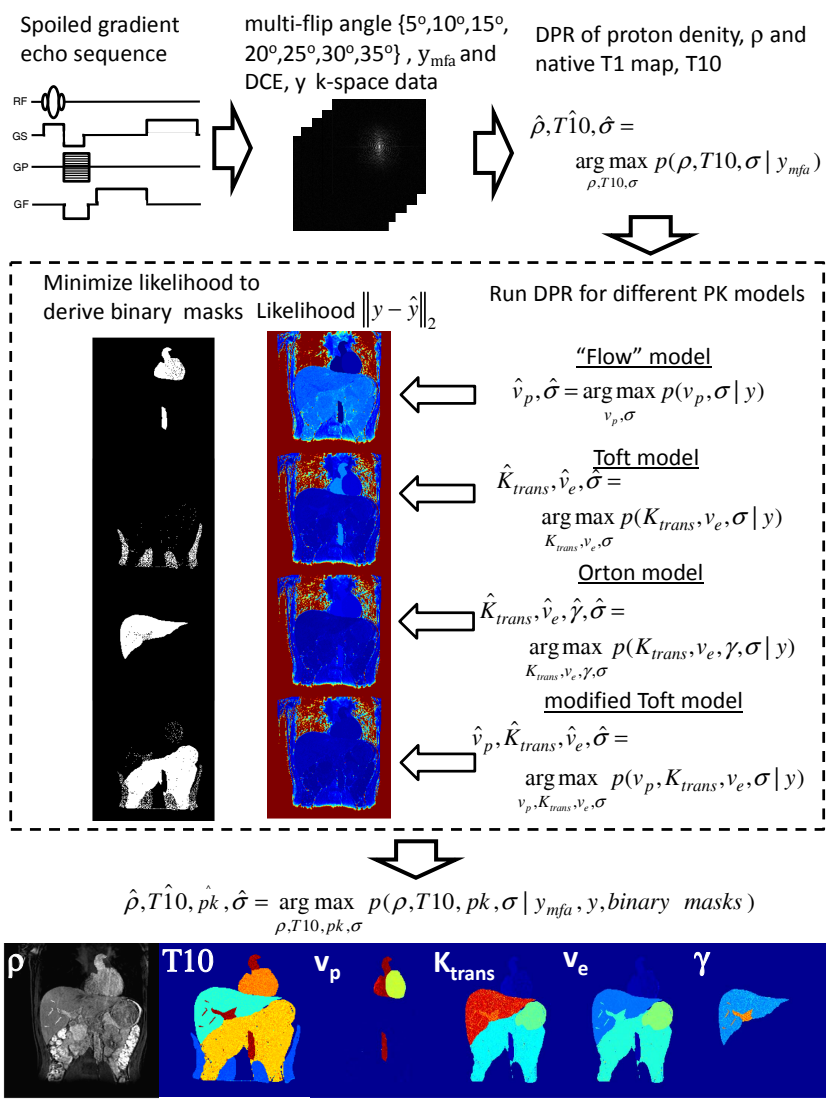

Figure1: Diagram of the different steps for the proposed implementation of DPR.

References: [1] N Dikaios et al, Medical Image Analysis 01/2014; 18(7): 989-1001. [2] PS Tofts Journal of Magnetic Resonance Imaging. 1997; 7, 91–101. [3] H Jung et al, Phys. Med. Biol. 2007; 52, 3201–3226. [4] MR Orton et al, Phys Med Biol. 2009;54(7):2197-215.