Bayesian estimation of multicomponent T2 distributions with stimulated echo compensation

Kelvin J. Layton[1,2], Mark Morelande[1], David Wright[3], Peter M. Farrell[1], Bill Moran[1], and Leigh A. Johnston[1,3]
[1]*Electrical and Electronic Engineering, The University of Melbourne, Parkville, Victoria, Australia,* [2]*National ICT Australia, Parkville, Victoria, Australia,* [3]*Florey Neuroscience Institutes, Parkville, Victoria, Australia*

TARGET AUDIENCE Researchers with an interest in T_2 mapping.

PURPOSE There is increasing interest in quantifying the distribution of T_2 values in each voxel of the brain, underpinning emerging techniques such as myelin water imaging used to study multiple sclerosis [1]. Two distribution models are commonly used: a pseudo-continuous grid, estimated using a non-negative least squares (NNLS) algorithm [2], and a multicomponent discrete distribution, estimated using nonlinear least squares [3]. It was recently demonstrated that a gradient-based nonlinear least squares algorithm is unreliable for the discrete distribution model and an alternative Bayesian algorithm was proposed [4]. Here we extend the method to include the extended phase graph (EPG) algorithm [5] to model stimulated echoes (arising from non-ideal refocusing pulses) for a multicomponent T_2 distribution. The EPG algorithm for stimulated echo compensation has been implemented for NNLS [6] and for single component decays with inhomogeneous slice profiles [7]. We use the EPG algorithm for a model with multiple discrete components (Eq. 1).

THEORY

$$y_n = \sum_{i=1}^{2} w_i \, EPG_n(\tau_i, T_1, \alpha) + v_n. \qquad (1)$$

In this equation, y_n is the amplitude of the n^{th} echo, w_i and τ_i are the weights and T_2 values of the i^{th} component, *EPG* denotes the extended phase graph algorithm, α is the flip angle, T_1 is the transverse relaxation time and v_n is assumed to be Gaussian noise.

METHODS Experiments were performed on a 4.7T Bruker BioSpec small bore MRI scanner fitted with a cryogenically cooled surface coil. A multi-echo CPMG sequence with 24 echoes was run with a first echo time of 12ms and an echo spacing of 12ms. All data was processed offline using MATLAB. T_1 is assumed to be 1s for all voxels. **Optic nerve sample**: A sample was prepared with agar gel and a sheep optic nerve fixed parallel to the transverse plane. The slice thickness was 1mm with TR=2500ms, FOV=6.4mm×12.8mm with a 64×128 matrix. Data was processed with the Bayesian algorithm [4] using both the multi-exponential model (assuming ideal 180° flip angles) and the multicomponent EPG model. The B_1 map estimated from the echo data was compared with the method in [8]. **Ex vivo mouse brain***:* A mouse brain was scanned with TR=2500ms, FOV=15mm×15mm, matrix=192×192. Data was processed using the proposed algorithm and NNLS [6]. For the NNLS data, the fast component of the distribution was calculated using the geometric mean of values below 40ms.

RESULTS Fig. 1a presents the slow and fast components of the T_2 distribution generated from the Bayesian algorithm with stimulated echo correction. The fast component exhibits similar T_2 values along the length of the nerve despite the flip angle variation. Conversely, the multi-exponential model in Fig. 1b only produces reasonable results in the region where the flip angle is close to 180°. The B_1 map estimated by the algorithm demonstrates good agreement with the measured map (Fig 2.). The spatial variation in the B_1 map is characteristic of a surface coil. Fig. 3 displays the weights and T_2 values of fast component of the mouse brain voxels. NNLS estimates a stronger weight of the fast component for white matter (indicated by arrows) while estimating a constant T_2. The minimal structure in the T_2 map is suggestive of strong regularization and may bias studies that use these distributions. Conversely, the proposed method demonstrates changes in both weight and T_2 of the fast component for white matter regions, which may improve future quantitative studies.

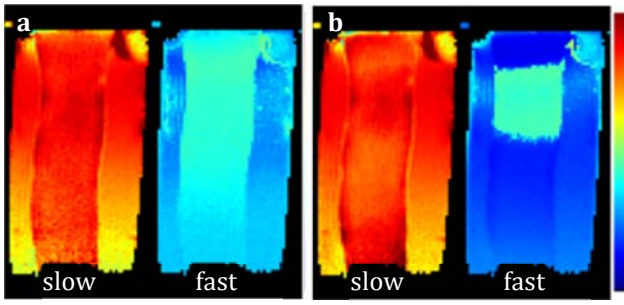

Fig. 1 Multicomponent T_2 maps (ms) of an optic nerve sample estimated using (a) the EPG model and (b) the exponential decay model. The left and right sides display the slow and fast components, respectively.

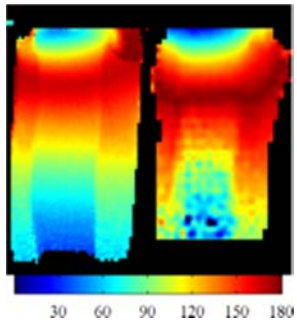

Fig. 2 The B_1 map estimated from the multi-echo data (left) and measured from separate spin echo images (right).

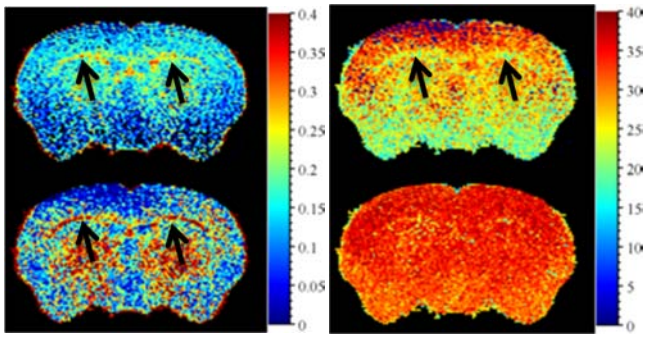

Fig. 3 Weights (left column) and mean T_2 (ms) (right column) of the fast component of a multicomponent T_2 distribution fit to mouse brain data. The arrows indicate white matter regions

CONCLUSION This work has presented a viable method to quantify the T_2 distribution of a voxel in the presence of flip angle inhomogeneity. The method extends the single component EPG model to multiple components and uses a Bayesian algorithm to provide robust parameter fitting. Further research is required to analyze the differences between the NNLS algorithm and the proposed algorithm.

REFERENCES [1] Laule. J Neurology 2004; 251:284-293 [2] Whittall. J Mag. Res. 1989; 84:134-152 [3] Andrews. MRM. 2005; 54:449-454 [4] Layton. ISMRM 2012; #2395 [5] Hennig. J Mag. Res. 1988; 78:397-407 [6] Prasloski. MRM. 2012; 67:1803-1814 [7] Lebel. MRM. 2010; 64:1005-1014 [8] Wang. MRM. 2005; 53:408-417